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SELECTING REMEDIATION TECHNOLOGIES
THROUGH A "TECHNICAL RISK" INDEX
An Application of Multi-Attribute Utility Theory

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This study applies multi-attribute utility theory to the DOE's problem of selecting the least risky technologies to develop. It focuses on two aspects of the technical risks involved with emerging technologies: the risk of successful development (measured by the likelihood of successful R&D completion within seven years) and the risk of successful implementation in the field (measured by the likelihood of the technology performing as anticipated). Three experienced contractors working with the Landfill Stabilization Focus Area served in the roles of DOE technology managers. Their preferences, expressed as MAUT utility functions, were assessed for all seven functional remediation processes. These utilities are plotted as three-dimensional surfaces over a plane formed by the two technical risk measures, graphically depicting the trade-offs each "decision maker" felt was appropriate between the two measures. Their utility surfaces for treatment technologies were then used with a set of ten treatment methods for which expert estimates of the two risk measures were available. The resulting rankings of technologies are analyzed to examine the suitability of the methodology. Recommendations for the use of this approach with real DOE managers are presented.

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ABSTRACT

To achieve the long-term environmental restoration objectives of the Department of Energy, the Office of Technology Development is developing remediation technologies that are better, faster, safer, and more cost effective than those currently available. These innovative technologies approach the state-of-the-art, with commensurately more risky development efforts than with more established technology. This study applies multi-attribute utility theory to the DOE's problem of selecting the least risky technologies to develop. It focuses on two aspects of the technical risks involved with emerging technologies: the risk of successful development (measured by the likelihood of successful R&D completion within seven years) and the risk of successful implementation in the field (measured by the likelihood of the technology performing as anticipated). Three experienced contractors working with the Landfill Stabilization Focus Area served in the roles of DOE technology managers. Their preferences, expressed as MAUT utility functions, were assessed for all seven functional remediation processes. These utilities are plotted as three-dimensional surfaces over a plane formed by the two technical risk measures, graphically depicting the trade-offs each "decision maker" felt was appropriate between the two measures. Their utility surfaces for treatment technologies were then used with a set of ten treatment methods for which expert estimates of the two risk measures were available. The resulting rankings of technologies are analyzed to examine the suitability of the methodology. Recommendations for the use of this approach with real DOE managers are presented.

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1.1 *Background*

Although positive steps have been taken during the past thirty years to remedy the nation's environmental problems, many challenges remain. To continue to address these challenges, the U. S. Department of Energy (DOE) has been implementing an aggressive national program of applied research that encourages the development of technologies to meet restoration and waste management needs, with highest priority being given to DOE's most pressing major environmental management problems. The keystone of DOE's approach is to develop remediation technologies that are better, faster, safer, and more cost effective than those currently available [DOEa, 1995a:vii-viii]. These innovative technologies approach the frontier of the current state-of-the-art. For this reason, DOE lacks historical data on which to base predictions of the proposed technologies' eventual successful development. As these technologies progress toward eventual employment, the DOE will be driven by limited budgets to fully fund only the most promising approaches. Estimating the new technologies' future performance is of crucial importance to DOE funding decisions, despite the difficulty involved.

Risks, to a program manager, relate to delivering a specified product or level of performance at a specified time for a specified cost. A wide variety of problems can prevent the meeting of these cost, schedule, and performance objectives. Failure to meet these goals, and the anticipated probability of that failure, form the risk in the program.

While there are other sources of program risk, including management difficulties, funding delays, and other circumstantial effects, a great deal of risk can be associated with the technology being developed itself. The attempt to provide a new or greater level of performance than previously demonstrated, or a similar level of performance subject to some new constraints of budget, packaging, or time, carries with it the possibility of failure with the consequence of lost time and money. This risk is generally referred to as "technical" or "technological risk," and is of critical importance to projects trying to improve on the state-of-the-art [DSMC, 1989:3-3].

One important concern of program managers investing in these innovative remediation technologies is "Will it work, at least as well as specified?" Since we cannot truly know this until the technology has been fielded, we are forced to rely on expert judgement and modeling to form estimates of the eventual level of performance.

The decision, however, is not as simple as merely choosing the technologies most likely to succeed in the field. Some technologies may have excellent potential for remediation use, but may rely on advances in the state-of-the-art that are only now being proposed or developed. These technologies may not be ready for field use for many years, and so may not be the right choice for certain sites despite their expected usefulness.

This study concerns itself with the tradeoffs between these two important technical risks — the risk that a technology may not be successful in real-world use, and the risk that a technology will not be successfully developed in time for some expected application. A manager facing the decision of investing in tomorrow's remediation solutions will value technologies with different estimated risks based on his or her personal preferences formed by past experience and

present circumstances. But even a veteran DOE manager may have difficulty choosing between many candidate technologies with similar estimated risks.

This report describes the use of multi-attribute utility theory to assist in such a decision, by forming a mathematical model of the manager's preferences and using that model to distinguish between candidate technologies. This model is not meant to replace the manager's judgement, but to clarify the technical risk aspect of the technology selection decision. He or she must examine other issues, such as funding limitations, timeliness, political concerns, and so on, in addition to each technologies' technical risk when making the decision. These other issues could also be the subject of similar utility models as desired.

After some background discussion of methodology, models developed for three different "decision makers" will be described. These "decision makers" were actually contractors working for the Landfill Stabilization Focus Area field office at the Savannah River Site in Aiken, South Carolina. They were interviewed in early December 1995 to assess their own preferences for various levels of the technical risk criteria already described. The models of these collected preferences will then be used on the technology selection decision posed in Figure 1.1. The ten treatment technologies shown on the diagram were selected by Dr Paul Krumrine of the Waste Policy Institute for this sample decision problem because estimates of the probabilities of successful development and use were easily gathered. Four different estimates of these attributes were used to rank order the candidate technologies with respect to the three different decision makers' preferences. The results of these twelve combinations of estimates and preference models will then be discussed.

1.2 *Methodology*

Figure 1.2 describes the overall approach to the technology selection problem in Figure 1.1. The heart of the matter is diagrammed in Figure 1.3. Given a time horizon and a list of technologies to examine, expert opinion is used to develop estimates of the two technical risk factors for each technology. Then the preferences of our decision maker are modeled mathematically, resulting in numerical expressions of the technical risk value of these technologies with respect to these technical risks. The overall score incorporates the trade-offs between the two risk factors that are acceptable to the decision maker. The technical risk factors are also called "attributes" in the context of multi-attribute utility theory.

1.2.1 *Attributes.*

1.2.1.1 *The risk of successful development, P(dev).* There is no guarantee that an ambitious technological approach will be successful — one estimate of the likelihood of technical completion for commercial R&D projects is **60%** [Bhat, 1991:262]. However, since the DOE is taking a long-term view with its applied research program, it is appropriate to consider the probability that a technology has completed its development as a function of time. The probability of successful development is then the probability that the technology in question has been released from R&D and is available for application. This "release date" is defined as when the given technology has satisfied all of its specified performance criteria and is considered ready for use in the field.

Example Technology Selection Decision

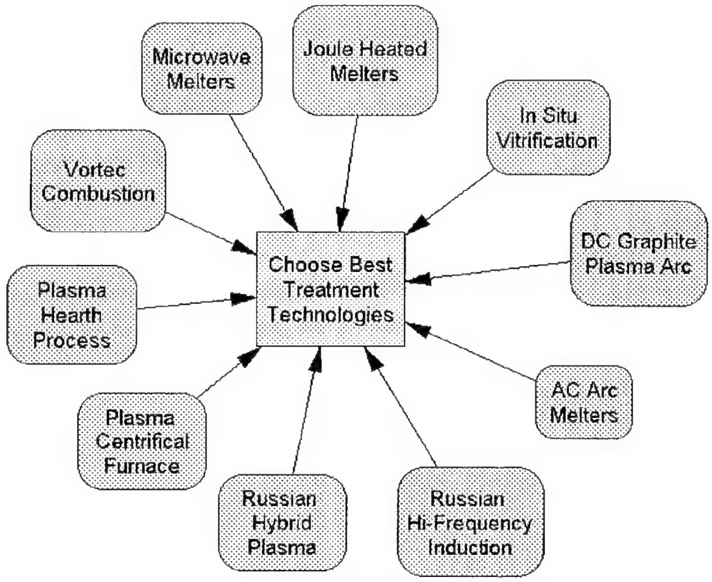


Figure 1.1

Basic Methodology

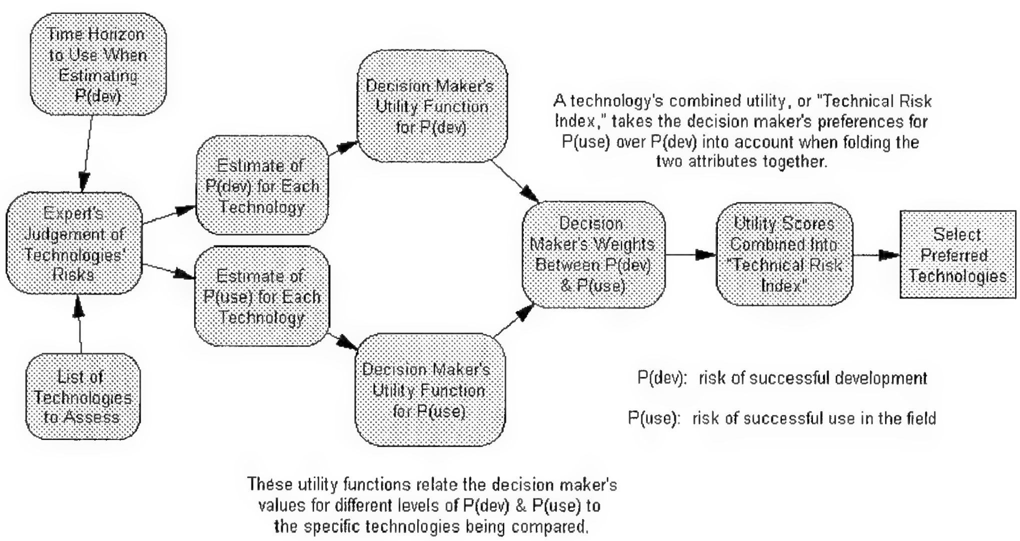


Figure 1.2

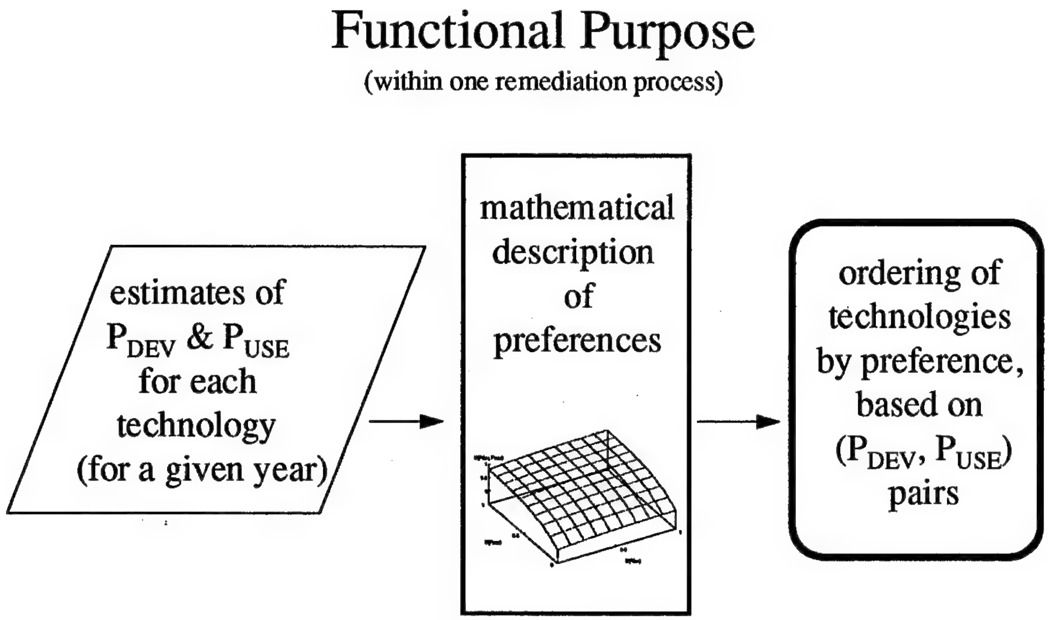


Figure 1.3

A technology will therefore be considered "successfully developed" after this release date, after the point when the technology has met whatever test and demonstration standards that mark the final stage of R&D.

1.2.1.2 *The risk of successful use, P(use).* The transfer from successful development to successful implementation is a step whose importance is often underestimated. Even if a technology has passed all of its developmental test and evaluation (DT&E) requirements, there is still no guarantee that it will move satisfactorily to the field. The controlled environment utilized in DT&E rarely represents real-world conditions. Often the situations where the technology is put to use are different from those anticipated by the original technology developers [Leonard-Barton, 1987]. To account for these possibilities, it is necessary to estimate the likelihood that a remediation technology is successful in the field, given that it was

successfully developed in R&D. This "implementation success" depends on many factors, some site dependent, most of which are unknowable at the present. Nevertheless, some estimate of this implementation success is arguably the most important criterion in judging between candidate technologies.

1.2.1.3 *Independence of the attributes*. By defining P(use) as the probability of successful use conditional on the technology being first "successfully developed," we can consider the two attributes, the probabilities of development and implementation success, as being independent. P(use) is the likelihood that the technology works as planned once it has completed R&D, however unlikely it is that that technology could be ready for use within the given time horizon. By accepting the assumption that the test and demonstration standards which a "successfully developed" technology must meet remain essentially unchanged through its multi-year R&D, we can say that its P(use) is then not dependent on either time or P(dev). For a time horizon farther out in the future, one would expect estimates of P(dev) to increase, but not P(use).

1.2.2 *Types of Technologies*. The complete remediation process, including a choice between containment and removal-treatment-disposal strategies, is shown in Figure 1.4. This paradigm of landfill remediation, taken from a discussion with Dr Jaffir Mohuidden in August 1995, establishes seven possible types of remediation technologies under consideration by the DOE Landfill Stabilization Focus Area. The decision maker could have very different values for the same levels of P(dev) and P(use) between two types of technologies. Potentially the decision maker may have 14 different sets of preferences, two for every combination of technology type.

1.2.2.1 *Characterization and Assessment.* These technologies identify, quantify, and locate waste. Characterization of the site is necessary to determine the boundaries of the waste and identify and locate specific waste forms and items, such as drums, large metal objects, and voids. Surveying and testing results in a site contamination map which is used to plan the rest of the remediation activities [DOEa, 1995:xiv]. The non-intrusive characterization of waste containers is also necessary to qualitatively and quantitatively determine the waste contents [DOEb, 1995:8].

1.2.2.2 *Stabilization.* Stabilization of waste in situ alters the waste's physical, chemical, and toxicological properties and prevents migration of waste outside the site boundaries [DOEa, 1995:xvi]. This process is similar to containment but is more temporary in intention, delaying the need for treatment and allowing for different remediation alternatives [Mohiudden, 1995].

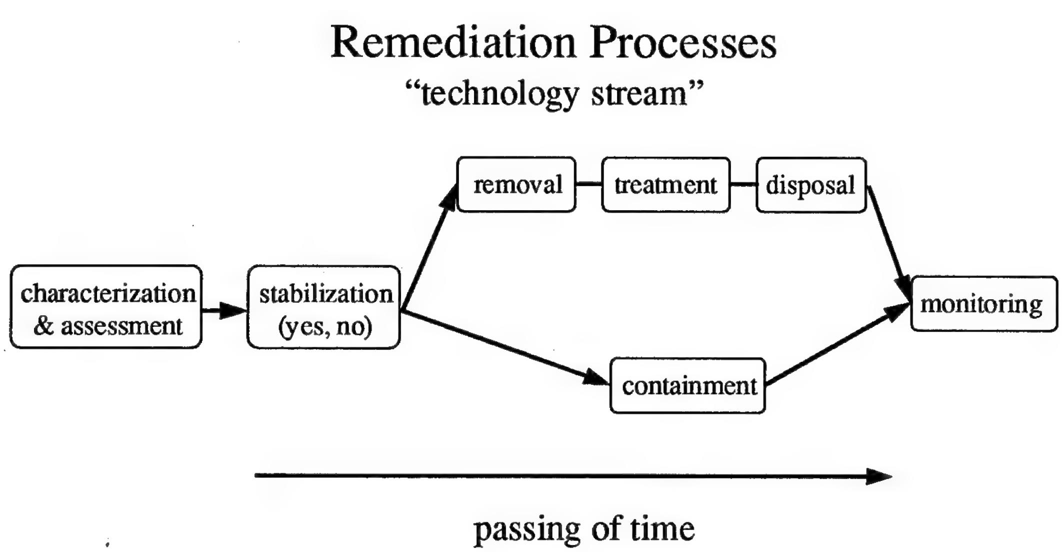


Figure 1.4

1.2.2.3 *Removal.* Also called *retrieval*, this involves excavation of waste and contaminated soil for ex situ treatment and disposal. For on-site treatment, treated decontaminated soil may be back-filled instead of disposed of off-site. Full-scale removal typically involves conventional drilling and excavation equipment, although remotely operated equipment and other alternatives are being developed [DOEb, 1995:xiv-xv].

1.2.2.4 *Treatment.* There are both ex situ and in situ treatment alternatives. For ex situ technologies, the waste debris and soil is packaged and transported to a treatment facility once it has been characterized and exhumed. There different processes will immobilize, detoxify, reduce waste volume, and/or stabilize the retrieved waste and soil for disposal on-site or at an off-site storage facility. In situ treatment methods act on localized and isolated waste cells to treat or stabilize the waste in place [DOEa, 1995:xv; DOEb, 1995:12-13].

1.2.2.5 *Disposal.* After treatment, stabilized final waste forms that are not back-filled at the original site must be transported to another site for disposal. Disposal technologies are used to keep the treated waste isolated from the environment [DOEa, 1995:xv; Mohuidden, 1995].

1.2.2.6 *Containment.* Containment is the restriction or confinement of buried waste to a limited area in order to prevent the migration or leeching of waste beyond the confinement boundaries. Placement of various barriers around the waste is determined by site and waste characterization data. Containment has a more permanent connotation than stabilization, although long-term containment may still serve as an interim action to prevent contaminant migration pending future remediation [DOEa, 1995:xv; Mohuidden, 1995].

1.2.2.7 *Monitoring*. All processes use monitoring devices to assess waste being handled and watch for inadvertant migration. Long-term monitoring of the original waste site and final disposal location are still required to ensure that no additional remedial action is needed in the future [Mohuidden, 1995].

1.2.3 *Utility Curves and Preferences*. When a decision maker's preferences for one attribute are examined, for example P(dev), a utility function for that attribute is assessed. A utility (or value) function for a decision as is meant here is a scalar index of a decision maker's value across the set of possible alternatives. The utility function allows the comparison of various levels of the attribute with respect to the actual value that the decision maker places on those levels, instead of the levels themselves. In this case, the nominal range of possible alternatives goes from 0% to 100%. A utility function for P(dev) assigns a value to every possible estimate of P(dev) from 0% to 100% [Keeney, 1976:68]. This value is the "technical risk index" score for P(dev).

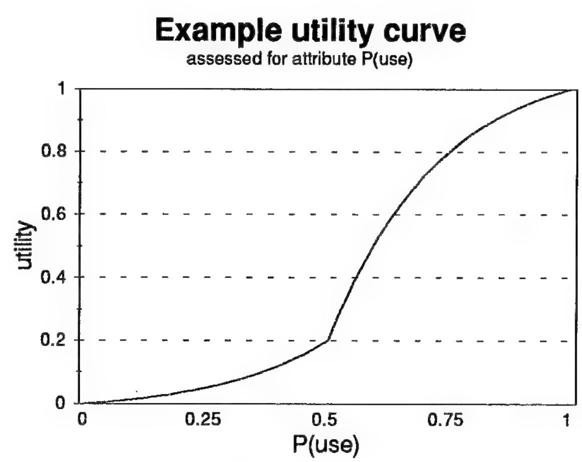


Figure 1.5

For computational reasons, the index of value that is developed from the utility function is normalized between 0 and 1. Of all the possible technologies, one with a P(dev) of 0 will be least preferred by a decision maker. That least preferred alternative is assigned a "0" utility. A technology with a P(dev) of 1 will be most preferred and so has a utility of "1". Once these "anchors" have been established, the remaining values then must be assigned for the other possible estimates for P(dev) between 0 and 1. The utility function must increase monotonically (that is, for two estimates p1 and p2 where p2 ≥ p1, the value of p2, U(p2), must always be greater than or equal to U(p1)). An example of a utility function is shown in Figure 1.5.

1.2.4 *Multi-Attribute Utility Theory.* Once utility functions for the two attributes are assessed, they can be combined to form an overall value score for that specific alternative. If the utilities have been assessed and combined correctly, the ordering of a set of alternatives based on their utilities will be the same as the order the decision maker actually prefers (so long as the decision maker remains consistent in his preferences).

The heart of the matter is then to combine the two single-attribute utility functions into one final value score or index allows us to see exactly the sorts of trade-offs the decision maker is willing to make to get the best alternative available. This establishes what combinations of the two attributes to which the decision maker is indifferent. While more complicated functional forms exist, two simple functions, the additive and multilinear utility functions, sufficiently represent decision maker preferences in most cases [Stewart,1995:257]. Both will be used in this work.

1.2.4.1 *Additive utility function.* The additive utility function simply adds the two single attribute utility functions after weighting them by appropriate weights. For our two attributes P(dev) and P(use) (abbreviating them as P_d & P_u for brevity), the combined additive utility function is:

$$U(P_d, P_u) = k_d\, U_d(P_d) + k_u\, U_u(P_u) \tag{1}$$

where $U_d(P_d)$ is the single attribute utility function for P(dev) and $U_u(P_u)$ is the utility function for P(use). The two weights, k_d and k_u, must sum to one for the final combined utility to remain between 0 and 1. So $k_u = 1 - k_d$ [Clemen,1991:480-4]. The values of k_d and k_u indicate the relative importance or weight the decision maker places on the two attributes P(dev) and P(use). For example, if $k_d < k_u$, P(use) is considered more important. To use this multi-attribute utility function, only a single constant, k_d, must be assessed in addition to the original utility functions for P(dev) and P(use).

This type of multi-attribute utility function implies that P(dev) is *utility independent* of P(use) (and vice versa). That is, conditional preferences for estimates of P(dev) do not depend on the particular level of P(use). Put another way, the decision maker's preference between the alternative technologies A and B, A having (P(dev), P(use)) estimates of (p1, p0) and B having (p2, p0), only depends on p1 and p2 and does not change for any level of p0. This utility independence is the characteristic which allows us to meaningfully use single-attribute utility functions in the first place [Keeney,1976:226].

The additive utility function also implies that P(dev) and P(use) are *additive independent* [Keeney, 1976:229-32]. Consider the following example, to illustrate the concept for our decision problem. Suppose we have four possible candidate technologies: A with (p1, p3), B with (p2, p3), C with (p1, p4), and D with (p2, p4), where p1 < p2 and p3 < p4. When comparing technologies A and B, our decision maker would clearly prefer B because p1 < p2. Likewise he or she would prefer D over C. Additive independence means our decision maker would prefer B over A *the same amount* as D is preferred over C, measured in utility — that is, U(p2, p3) - U(p1, p3) = U(p2, p4) - (p1, p4).

Put another way, additive independence allows for no interaction between the decision maker's preferences for various levels of P(dev) and P(use). For example, under additive independence a technology with a P(dev) of .9 will always be preferred to one with a P(dev) of 0.8 in the same way whether both technologies have a P(use) of 0.1 or 0.95. While this condition is not true for most decision makers, often an additive utility function does well enough in modeling their preferences to justify using it [Clemen,1991:483; Stewart,1995].

1.2.4.2 *Multilinear utility function.* The multilinear utility function is a generalization of the additive function, where the requirement for additive utility independence is relaxed and interactions between the attributes is allowed. Mutual utility independence is still required, however. The form of the function is:

$$\mathrm{U}(P_d, P_u) = k_d \mathrm{U}_d(P_d) + k_u \mathrm{U}_u(P_u) + (1 - k_d - k_u) \mathrm{U}_d(P_d) \mathrm{U}_u(P_u) \qquad (2)$$

using the same notation as with equation 1. Note that the only differences are that 1) $k_u \neq 1 - k_d$ and 2) an interaction term has been added [Keeney,1976:233]. The impact of the interaction term is set by the two constants, k_d and k_u. The greater the magnitude of the $(1 - k_d - k_u)$ term, the greater the effect of the interaction. If the $(1 - k_d - k_u)$ term is zero, the multilinear function defaults to the additive utility function already discussed [Clemen,1991:481].

When assessing a multilinear utility function, only one more step is needed beyond the assessment of an additive function. An additional trade-off between two alternative technologies is made, where one alternative is set with a given (P(dev), P(use)) estimate while the other's attributes are allowed to vary. The decision maker is asked to set the second technology's P(dev) and P(use) at a different pair of levels where he or she would be indifferent between the two candidate technologies. The answer to this question provides the necessary additional information to establish the multilinear utility function.

1.2.4.2.1 *Substitutes and Complements*. The interpretation of this additional term $(1 - k_d - k_u)$ is not as straightforward as that of the two weights k_d and k_u. If this term is positive, high values of P(dev) and P(use) raise the overall utility higher than the two additive terms alone. Then the attributes are called *compliments* of each other. A low estimate of one will severely reduce the combined overall utility. One low estimate is almost as bad as having two, and a high utility is only found by high estimates of both. If $(1 - k_d - k_u)$ was negative, the two attributes are *substitutes* for one another. Here high values of both result in a large product term that is subtracted from the additive total. In a sense, preferred values of P(dev) and P(use)

work against each other. But when one is high and the other low, the subtracted term is not very large. This means the overall utility can still be reasonably high despite one attribute being low.

Example Indifference Curves

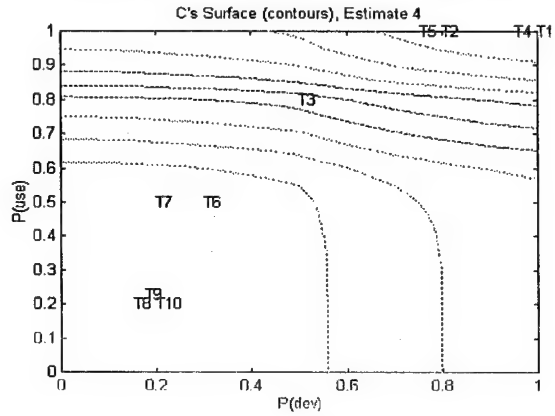


Figure 1.6

1.2.5 *Indifference Curves*. Once the multi-attribute utility function has been assessed, the mathematical model of the decision maker's preferences can now be expressed. One tool for looking at these preferences are *indifference curves*. These curves are plotted on a graph with P(dev) on one axis and P(use) on the other, and show the sets of technologies whose total combined utility is the same. The decision maker will be indifferent between any technologies whose P(dev) and P(use) attributes place them on the same line on the basis of the two technical risk factors. See Figure 1.6 for an example where different possible alternatives (T1 through T10) are graphed along with the indifference curves. Each of the lines, going from lower left to the upper right, represents utilities of 0.1, 0.2, 0.3, and so on. Graphing indifference curves provides insight into the decision maker's trade-offs between the two attributes [Clemen,1991:442].

1.2.6 *Utility Surfaces*. Plotting the combined utility as a three-dimensional surface above the plane provided by the two attributes as axes can provide another visualization of the decision maker's preferences. These surfaces are closely related to the indifference curves introduced above — the indifference curves are merely the contours of the utility surface. These three-dimensional graphs are the most clear representation of complex preference relationships between two attributes. See Figure 1.7 for an example. Each color represents a band of utilities, climbing from 0 to 0.2 (blue), 0.2 to 0.4 (green), and so on.

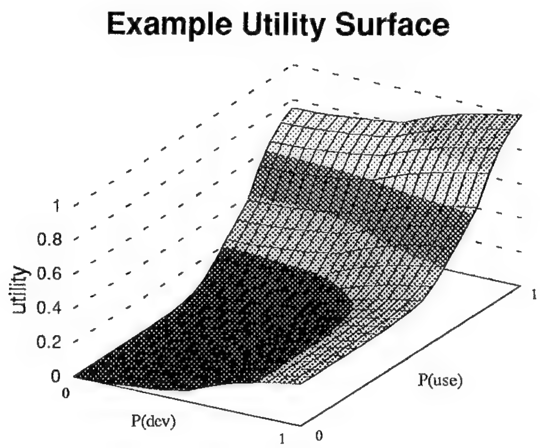


Figure 1.7

1.2.7 *Assessment Questions*. The first issue that was explored in the interviews with the three "decision makers" was the degree of additive and utility independence between P(dev) and P(use) for that person (this was done using an adaptation of a dialog in Keeney and Raiffa [1976:299-300]). As already mentioned, there is some tolerance for not strictly adhering to the requirements of additive and utility independence.

The interviewees were then asked questions first to establish their values across the possible ranges of P(dev) and P(use) and then to set the weights for their combined utility function. The interviews took from 45 minutes to two and a half hours to conduct, depending on the complexity of the interviewee's preferences. The dialog between interviewer andintervieweewas a learning process for both participants and proceeded quickly once both were comfortable with the assessment process and the interviewee's values.

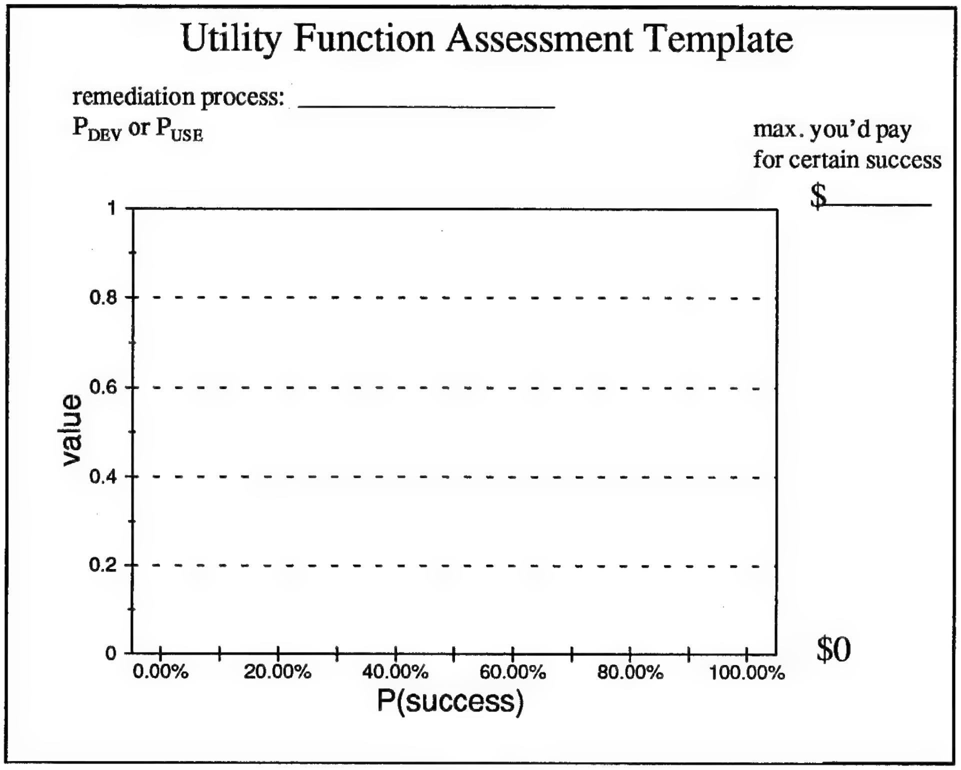


Figure 1.8

Assessing the single utility functions was done graphically, using the template shown in Figure 1.8. The technology type and attribute that was being assessed were first recorded (for example, "treatment technologies" and "P(dev)"). Often utility functions were the same for

several technology types, making the assessment process simpler. The interviewer and interviewee then agreed that the highest value (utility = 1) should be given to technologies which were certain to be available or be successfully used (P(success) = 100%). The interviewee was asked how much he or she would be willing to pay to buy such a technology, to reinforce a value-focused perspective. A lower limit of value would then be set for technologies that had no chance of successful development or use (P(success) = 0).

Once the endpoints of the value function were set, the interviewee was asked how much he would pay for a technology with only a 50-50 chance of being successfully developed or used. This corresponded to the utility of P(success) = 50%. Similar questions were asked to find other points on the utility function until the interviewee was satisfied with the shape. Once the interviewee had become familiar with this process, he could draw his value curves directly without much prompting.

After utility functions were assessed for all combinations of technology type and attribute, the interviewee was asked questions to determine the constants of his multi-attribute utility function. A computer software program, *Logical Decisions*©, was used to frame the necessary questions. For those interviewees whose combined utility function was additive, a simple pair of bars were used to establish relative weights between P(dev) and P(use). The decision maker could change the lengths of these bars until he felt they reflected the relative importance of the two attributes. For those with multilinear combined utility functions, one more question was asked to establish a trade-off as described in section 1.2.4.2. *Logical Decisions*© calculated the values of the constants from the answers to these questions.

The *Logical Decisions*© software was also used after the interviews were finished, to reproduce the hand-drawn single-attribute utility curves of the interviewees and determine the equations of the curves. These equations were then used in a spreadsheet to produce the graphs that follow. The final indifference curves and utility surface graphs in section 5.0 were produced using *Matlab*©.

II. *Preferences of the Example Decision Makers*

2.1 *The "Decision Makers"*

The methods described in the previous section can model the preferences of any waste remediation program manager to support technology investment choices. To illustrate their use, three experienced people working with the Landfill Stabilization Focus Area Field Office at the Savannah River site were interviewed and their utilities assessed. While these interviewees were not actual DOE managers, they each had experience working with these issues and supporting the Department of Energy. The three individuals each had a very different focus on what they considered most relevant for technology decisions. Utility functions for all the types of remediation technology were assessed and are graphed below.

Since the identities of the interviewees are irrelevant for this report, they are labeled "A," "B," and "C."

The time horizon used to frame the technology selection preferences for P(dev) was seven years from now (Dec 1995), as selected by Dr Paul Krumrine. The utility functions assessed for P(dev) are only valid for this time frame. Additional assessment would be required to examine different horizons for technology investment preferences.

2.2 *A's Preferences*

Interviewee A had a very simple perspective of a technology's value to the Department of Energy. He believed that no technology was worth anything to DOE unless it had a predicted 75% chance of being ready within seven years or an predicted 75% chance of successful

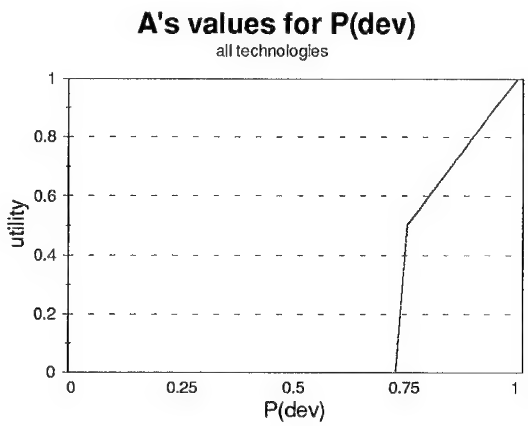


Figure 2.1

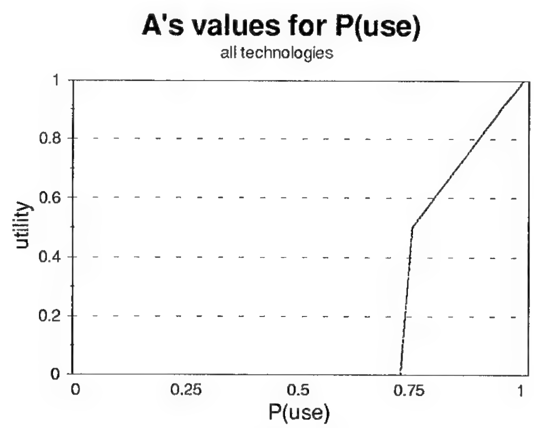


Figure 2.2

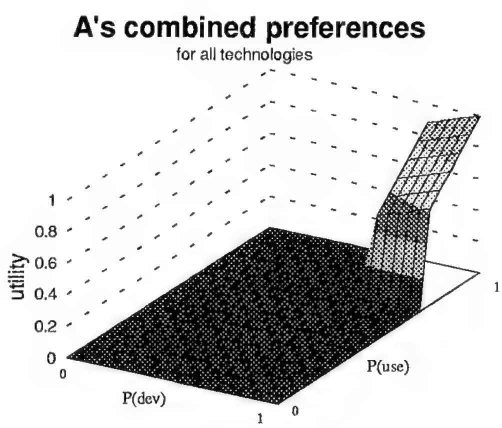


Figure 2.3

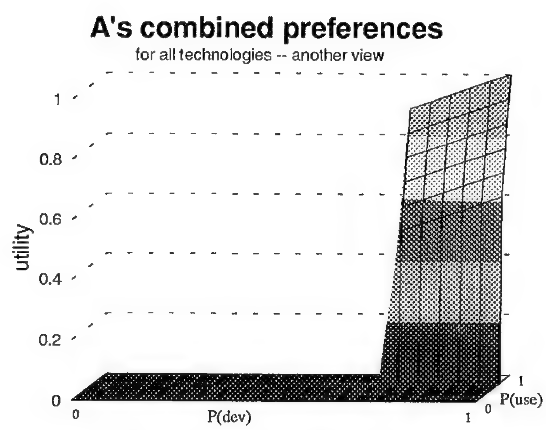


Figure 2.4

implementation in the field. The pressure from complying with current remediation agreements and budget constraints would leave DOE with no other options but the more certain technologies.

The following graphs, Figures 2.1 and 2.2, show his two utility functions for all technology types. His preferences for P(dev) and P(use) place no value on technologies with less than an estimated 75% chance of being available or working as expected (the slope of the increase in value at 75% in both graphs is an artifact of the graphing software — the actual utility function has a discontinuity at 75%, where the utility goes from 0 to 0.5). Above his 75% threshold, however, he felt that his values scaled linearly with increasing likelihood of success.

A had an additive multi-attribute utility function and placed more value on P(use) than on P(dev). His utility surface is graphed in figures 2.3 and 2.4. This "floor" of zero value for any technology that has an estimate beneath his 0.75 threshold shows how he would exclude anything but the minority of proven and nearly developed remediation technologies from consideration.

2.3 *B's Preferences*

B had recent experience dealing with actual waste site management and so had more of a landfill owner's perspective. He proved to have the most complex set of preferences, with a different utility function for almost every technology type. P(dev) and P(use) were not additively independent for B, and so a multilinear combined utility function was used.

B did not agree with the remediation process paradigm shown in Figure 1.4. He believed that the monitoring process could actually be one of the first stages, since other processes would only be needed at a landfill if waste was detected migrating out of it. This disagreement did not

invalidate either the approach to technical risk or the method of comparing technologies, since technologies should only be compared against others from the same process.

He also disagreed with the interviewer's assumption that a technology with zero chance of successful implementation would cost nothing (i.e. 0 utility = 0 cost), and correctly pointed out that failure in the field for critical processes could have negative value to the site owners. In a few cases he set the lower limit of his values for P(use) at a negative dollar value, with respect to the amount he would be willing to spend to buy a technology certain to succeed. This did not present any difficulty. These ranges of value were normalized to a 0 to 1 interval afterward to relate his values to a standard (0,1) utility, where his lowest negative dollar cost (for P(use) = 0) was assigned zero utility and the rest were scaled up from there. It is the shape of his value curve that is important, and was preserved.

B's single attribute utility functions are graphed below, in Figures 2.5 to 2.13. He grouped characterization, containment, stabilization, and removal technologies into one set with the same value function for P(dev). He also considered treatment and disposal technologies as having the same value function for both P(dev) and P(use). All other technologies were regarded individually by B.

B's utility functions are generally in the shape of S-curves, with some lower threshold of estimated success required before any significant value was placed on a technology climbing up to some upper threshold beyond which he is relatively indifferent. Unlike A, however, B believed

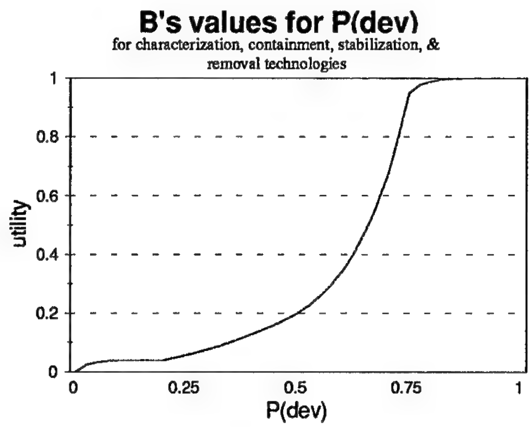
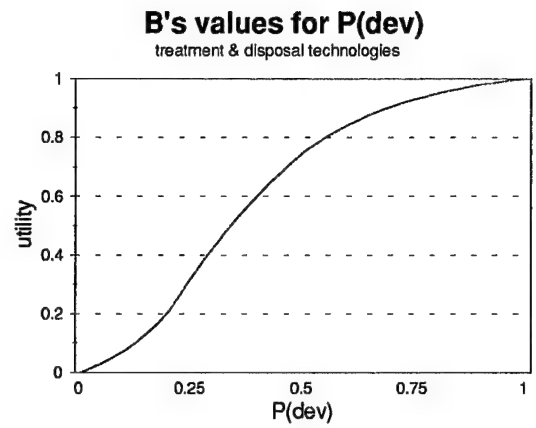


Figure 2.5



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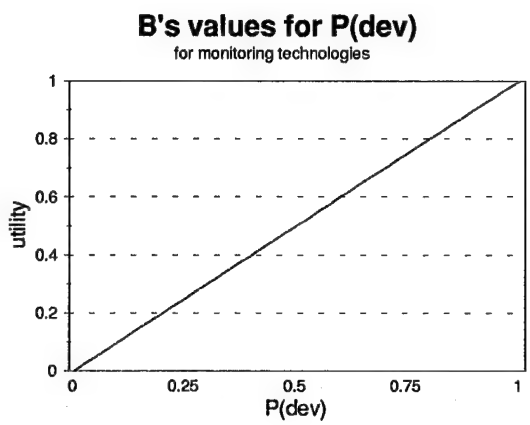
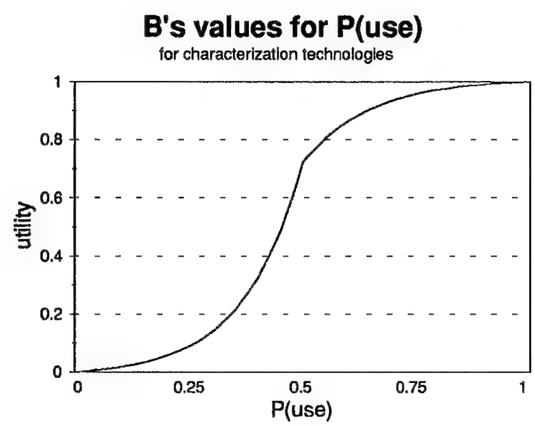


Figure 2.7



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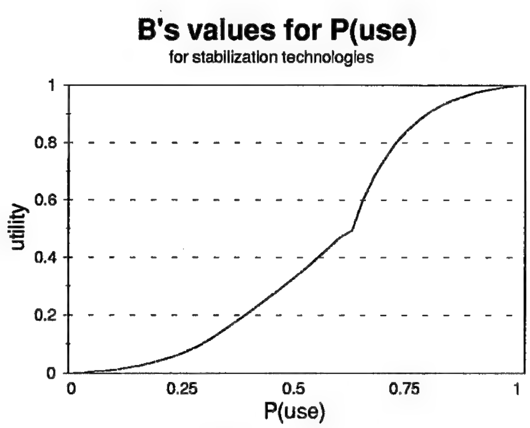


Figure 2.9

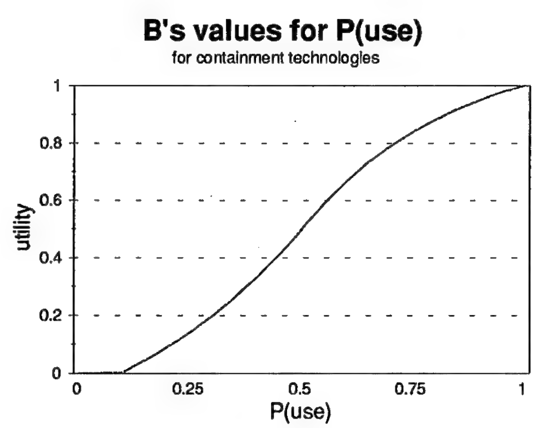


Figure 2.10

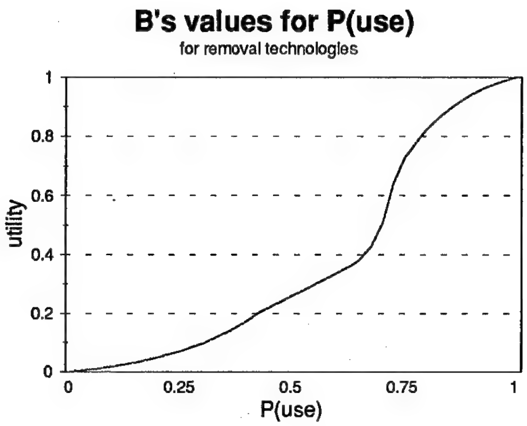


Figure 2.11

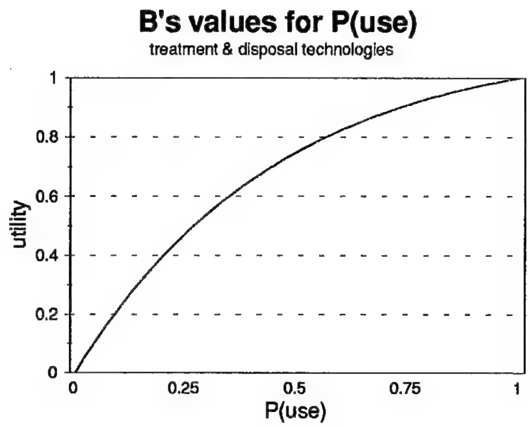


Figure 2.12

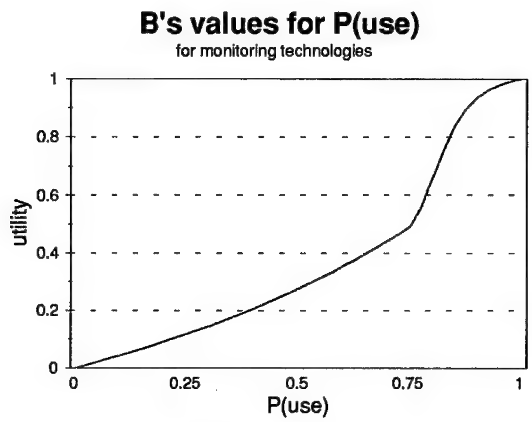


Figure 2.13

there was some value to working on technologies with little chance of successful development, depending on the type of technology.

B was more tolerant of lower likelihoods of successful development with treatment, disposal, and monitoring technologies. This is due to his beliefs that adequate methods for these processes already exist and, in the cases of treatment and disposal, that the processes themselves were not that crucial. For monitoring technologies, his utility function is simply linear (see Figure

2.7). Otherwise he placed nearly equal value on technologies with a P(dev) of between 75% to 100%, with a steep drop-off in value below that range (see Figure 2.5).

B's detailed preferences for P(use) are very interesting. He believed monitoring technologies to be the most important with respect to successful use, since any failures in the field could lead to neglecting waste migration and more difficult (and costly) remediation needs. Almost as important are successful removal technologies, since that is the most crucial step in the removal-treatment-disposal strategy for the owner of a waste site (since after removal the waste is out of the landfill and poses a much lower threat of contamination at the site). For both these types of technologies, B's utility curves give high value only to relatively high estimates of P(use) (see Figures 2.13 and 2.11, respectively). Stabilization and containment technologies had value functions more tolerant of lower likelihoods of success, since even partial successes would slow the leakage of waste from the site. B also felt that successful detailed characterization of the landfill's waste streams was not as significant, since successful removal and containment approaches did not necessarily depend on it.

B's utility function for treatment and disposal technologies has the most unusual shape — unlike the rest, it is just a simple concave exponential utility curve (see Figure 2.12). This fits his view that treatment and disposal are the least important remediation processes. Less than complete success here means little to the landfill manager, since the waste is no longer his responsibility.

B's multiattribute utility surfaces are all multilinear in form. He placed far more value on P(use) than on P(dev), consistent with his previous experience. His additional trade-off

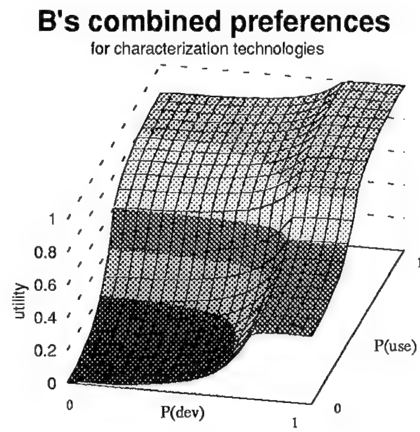


Figure 2.14

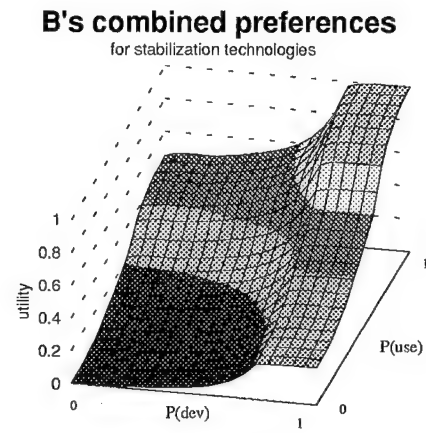


Figure 2.15

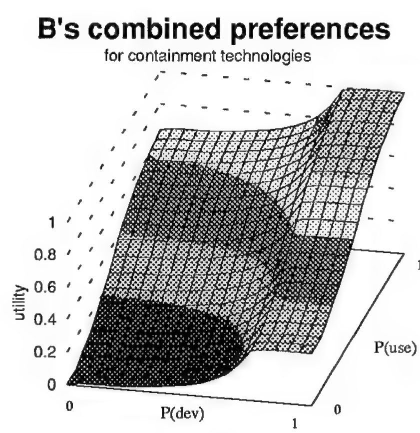


Figure 2.16

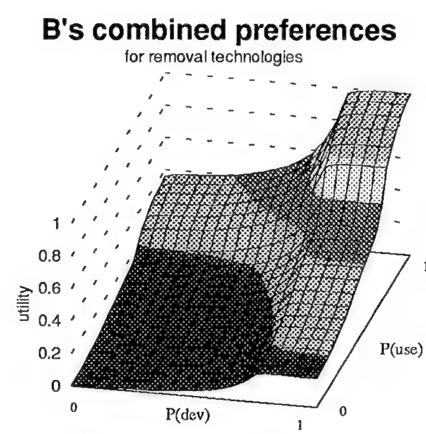


Figure 2.17

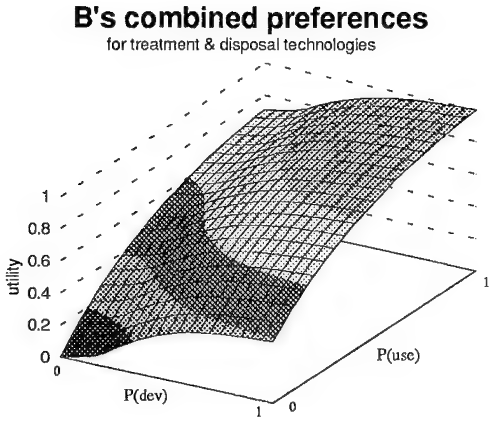


Figure 2.18

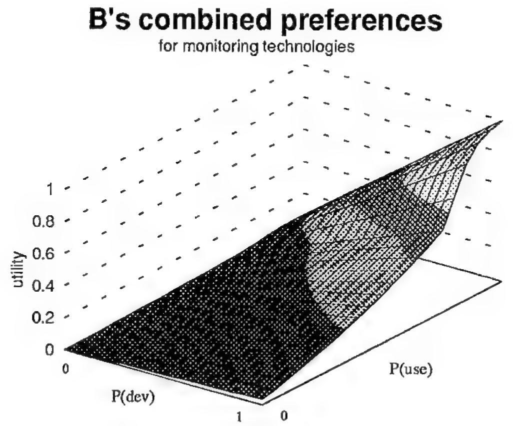


Figure 2.19

established the relationship between the single-attribute utility functions and the constants k_d and k_u. His various utility surfaces follow in Figures 2.14 through 2.19.

The small orange areas (total utility > 0.8) show B's opinions about the importance of monitoring and removal technologies (Figures 2.19 and 2.17, respectively). Only technologies with high P(dev) and P(use) estimates have high value to him in these crucial processes. Likewise, the gradual slope and broad orange area of B's surface for treatment and disposal technologies show how relatively indifferent he is to these processes (see Figure 2.18). One interesting thing to notice is how four out of B's surfaces (fig. 2.14-2.17) resemble A's discontinuous ones to some degree, despite having drastically different single-attribute utility curves.

2.4 *C's Preferences*

Unlike A's programmatic perspective or B's site management one, C had more of a technology developer's viewpoint. His experience in R&D for waste remediation was the source of his preferences. Figures 2.20 to 2.22 show his single attribute utility functions.

C has a vaguely S-curve utility function for P(dev), as is shown in Figure 2.20. He also disagreed with the interviewer's assumption that a decision maker would want to spend zero

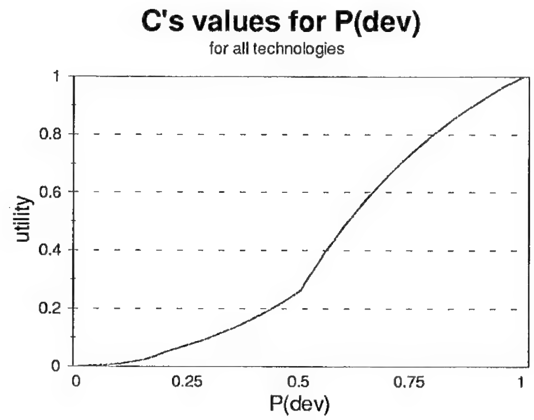
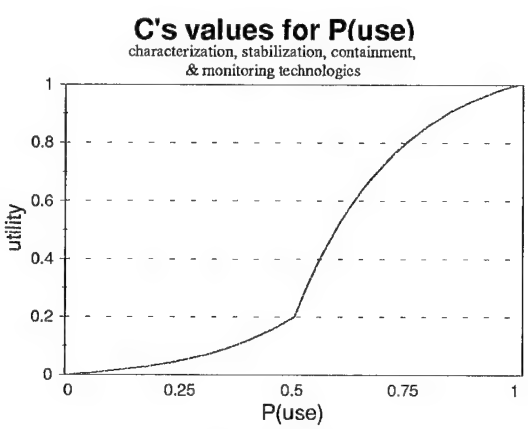


Figure 2.20



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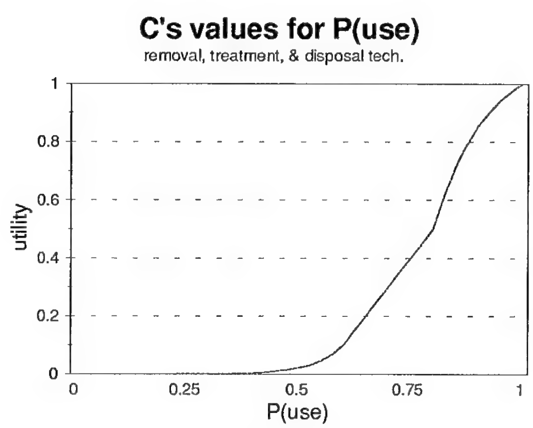

Figure 2.22

funds on technologies with no chance of being developed within the time horizon — he preferred to spend at least 5% of what he would pay for technologies certain to be ready on development efforts that would only pay off in the long term. His value curves were rescaled to fit a (0,1) standard utility range, just as B's were. Like B, C felt some remediation processes required different utility curves for P(use). He thought removal, treatment, and disposal technologies were too important to give much value to alternatives with poor estimated field performance (see Figure 2.22). He was more tolerant of less robust alternatives in the other remediation processes (see Figure 2.21).

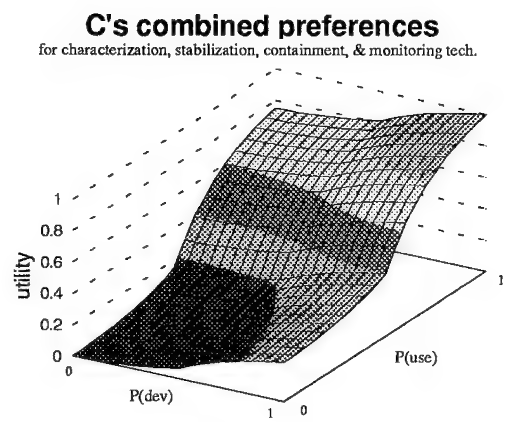

Figure 2.23

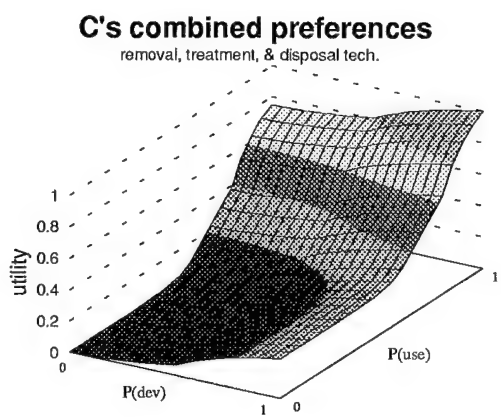

Figure 2.24

C, like B and A, thought P(use) was more important than P(dev). The differences between the curves in Figures 2.21 and 2.22 have a impact on the final utility surfaces for the two groups of technology types. C's relative intolerance for failure in the field for removal, treatment, and disposal technologies is evident in the greater slope of the surface in Figure 2.24. There is a smaller area of utility > .8 than in his other surface for characterization, stabilization, containment, and monitoring technologies (see Figure 2.23).

In general, C's surfaces show higher value for candidate technologies with high P(use) and low P(dev) estimates than the others. This reflects his views about funding technologies with higher development risk.

III. *Candidate Treatment Technologies*

3.1 *Example Technology Selection Problem*

It was decided to exercise the models of A, B, and C's preferences with an example decision problem of the sort faced by DOE technology managers. A recent review of a group of treatment technologies being developed through the DOE had just been conducted. Dr Paul Krumrine was able to ask a few attendees of this review to estimate the two technical risk factors for ten of these technologies. The definitions used in this report for probabilities of successful development and successful field use were explained and a time horizon of seven years was set. Dr Krumrine faxed these estimates to AFIT/ENS in December 1995.

By using the utility functions assessed for A, B, and C on treatment technologies, a ranking of the ten technologies based on the "decision makers'" preferences for these technical risk factors can be generated. Analysis of the results will help evaluate the usefulness of this approach.

3.2 *Technical Risk Estimates*

The estimates of P(dev) and P(use), designated 1 through 4, were made by four experts equipped with our definitions of P(dev) and P(use) for ten different treatment technologies currently under development by the Department of Energy. Hereafter we will refer to expert 1 as providing estimate 1, and so on. The candidate technologies are listed in Table 3.1 with the corresponding P(dev) and P(use) estimates. The table should be read, for Joule Heated Melters as an example, as saying expert 1 assessed the probability of this technology being ready within

seven years as 100% and the probability of successful field use as 75%. The codes are supplied for interpreting the graphs that follow.

P(dev) & P(use) Estimates for 10 Treatment Technologies P(dev) estimated for availability by 7 years from now		estimate 1		estimate 2		estimate 3		estimate 4	
	code	P(dev)	P(use)	P(dev)	P(use)	P(dev)	P(use)	P(dev)	P(use)
Joule Heated Melters	T1	100	75	95	95	80	75	100	100
DC Graphite Plasma Arc	T2	75	75	90	90	60	40	80	100
AC Arc Melters	T3	50	50	50	35	50	35	50	80
In Situ Vitrification	T4	75	25	70	60	70	60	100	100
Russian Hi-Frequency Induction	T5	75	25	20	30	10	10	80	100
Russian Hybrid Plasma	T6	50	25	20	50	15	15	30	50
Plasma Hearth Process	T7	25	25	50	40	40	30	20	50
Plasma Centrifical Furnace	T8	25	15	50	40	25	20	20	20
Vortec Combustion	T9	10	10	70	20	10	10	20	20
Microwave Melters	T10	10	10	20	10	10	10	20	20

Table 3.1

The four following graphs, Figures 3.1 to 3.4, depict each set of estimates in a different form. These plots will be superimposed on the utility surfaces of A, B, and C corresponding to treatment technologies in section 4.0 to graphically illustrate how these utilities generate rankings of the candidates. Please refer back to Figures 3.1 through 3.4 to help interpret the surface plots.

Note that several technologies have the same estimated P(dev) and P(use) and so should have the same resulting combined utilities.

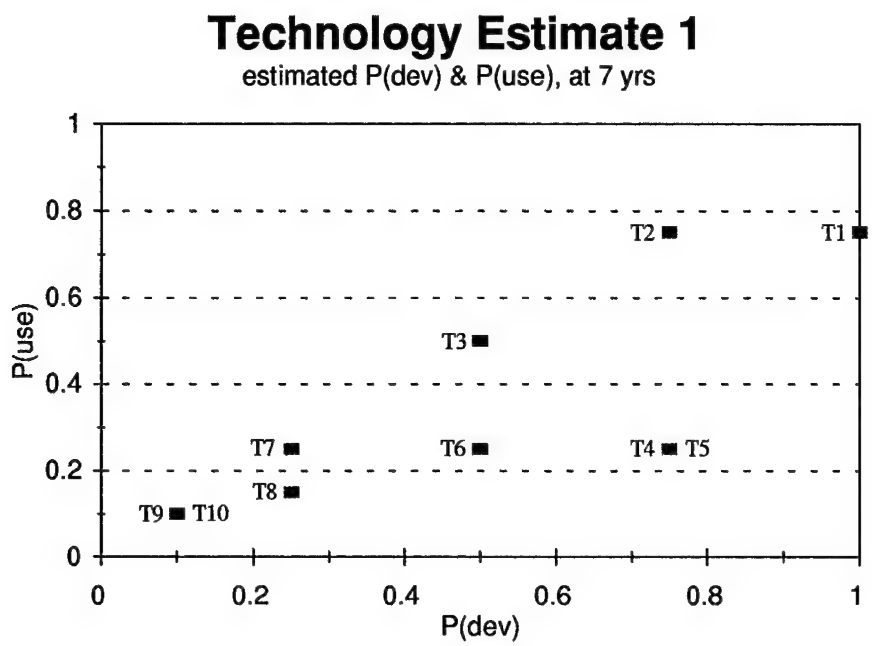

Figure 3.1

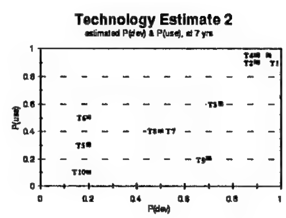

Figure 3.2

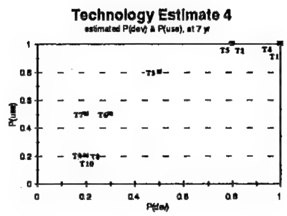

Figure 3.4

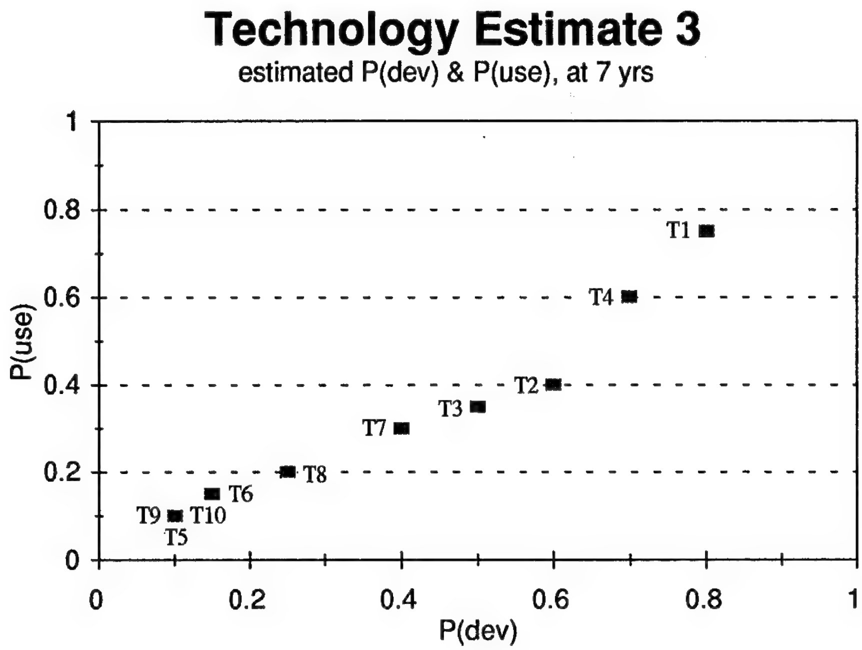

Figure 3.3

IV. *Results of Sample Decision Problem*

4.1 *Summary of Resulting Utilities*

Table 4.1 lists the resulting utilities of the ten treatment technologies for the 12 combinations of "decision maker" and technical risk estimate.

Combined Utilities

for each combination of preference and expert estimate of risk parameters

	A's preferences				B's preferences				C's preferences			
estimate:	1	2	3	4	1	2	3	4	1	2	3	4
Joule Heated Melters	.616	.9	.523	1.00	.944	.989	.931	1.00	.55	.945	.501	1.00
DC Graphite Plasma Arc	.5	.8	0	.907	.927	.974	.745	.988	.484	.866	.125	.951
AC Arc Melters	0	0	0	0	.780	.874	.684	.898	.082	.259	.067	.441
In Situ Vitrification	0	.877	0	1.00	.656	.986	.868	1.00	.185	.934	.241	1.00
Russian Hi-Frequency Induction	0	0	0	.907	.656	.482	.198	.988	.185	.014	.186	.951
Russian Hybrid Plasma	0	0	0	0	.600	.635	.289	.694	.066	.029	.006	.041
Plasma Hearth Process	0	0	0	0	.469	.720	.602	.635	.019	.069	.043	.029
Plasma Centrifical Furnace	0	0	0	0	.353	.720	.414	.377	.019	.069	.019	.013
Vortec Combustion	0	0	0	0	.198	.601	.198	.377	.003	.166	.003	.013
Microwave Melters	0	0	0	0	.198	.245	.198	.377	.003	.013	.003	.013

Table 4.1

The very different utility surfaces for A, B, and C shown in section III suggested that the combined utilities for treatment technologies would vary widely between the "decision makers." The results in Table 4.1 show this impression was correct. While those technologies with generally high estimates for both P(dev) and P(use) all tend to have utilities of 0.9 or more, the others' utilities differ considerably. C's utilities are all much lower than B's in these ranges of (P(dev), P(use)) pairs for the same estimate, sometimes by more than an order of magnitude. If one excluded all technologies whose utilities were less than 0.2, the set of these eliminated technologies would look very similar for both A and C. This suggests more parallels between A and C's values than their utility surfaces suggest.

Table 4.2 shows the resulting rank orderings of the different technologies organized by "decision maker," while Table 4.3 is organized by expert estimate. The "--" in the columns of A's results reflect the zero utilities generated by his utility function. Since there were many technologies whose attributes were estimated to be the same, there are ties inside several sets of rankings.

These rankings are surprising in their similarities, despite the differences in utilities from Table 4.1. Reviewing first rankings in the same estimate set, the rank ordering of technologies is consistently the same for the different "decision makers." The rankings are identical for all three "decision makers" in both estimate 3 and estimate 4, and only differ by a few interchanged positions in estimates 1 and 2. This suggests that the three "decision makers" were actually very consistent with each other's values, despite their different orientations (A - programmatic, B - waste site ownership, & C - technology development).

Rankings By "Decision Maker"

for each combination of preference and expert estimate of risk parameters

		A's preferences				B's preferences				C's preferences			
	estimate:	1	2	3	4	1	2	3	4	1	2	3	4
Joule Heated Melters	T1	1	1	1	1	1	1	1	1	1	1	1	1
DC Graphite Plasma Arc	T2	2	3	--	3	2	3	3	3	2	3	3	3
AC Arc Melters	T3	--	--	--	--	3	4	4	5	5	4	4	5
In Situ Vitrification	T4	--	2	--	1	4	2	2	1	3	2	2	1
Russian Hi-Frequency Induction	T5	--	--	--	3	4	9	8	3	3	9	8	3
Russian Hybrid Plasma	T6	--	--	--	--	6	7	7	6	6	8	7	6
Plasma Hearth Process	T7	--	--	--	--	7	5	5	7	7	6	5	7
Plasma Centrifical Furnace	T8	--	--	--	--	8	5	6	8	7	6	6	8
Vortec Combustion	T9	--	--	--	--	9	8	8	8	9	5	8	8
Microwave Melters	T10	--	--	--	--	9	10	8	8	9	10	8	8

Table 4.2

In review, the rankings by preference set in Table 4.2 show that the top four technologies remained consistently T1, T2, T3, and T4. Only once is T3 pushed back to #5 (C, estimate 1) because for that estimate and preference set T5 is valued more. The bottom technologies also stay mostly the same between B and C across the different estimates.

The only technology which changes place often is the Russian Hi-Frequency Induction method, T5. In some cases, T5 is one of the least preferred technologies, while in others it is in the top three or four. Its rank stays mostly consistent between "decision makers" inside one estimate, which suggests the different rankings has to do with very different risk estimates by the

four experts (a glance at Table 3.1 supports this). The ranking of T5 will be discussed in a later section.

Rankings By Expert

for each combination of expert estimate and "decision maker" preference

		expert 1			expert 2			expert 3			expert 4		
"decision maker:"		A	B	C	A	B	C	A	B	C	A	B	C
Joule Heated Melters	T1	1	1	1	1	1	1	1	1	1	1	1	1
DC Graphite Plasma Arc	T2	2	2	2	3	3	3	--	3	3	3	3	3
AC Arc Melters	T3	--	3	5	--	4	4	--	4	4	--	5	5
In Situ Vitrification	T4	--	4	3	2	2	2	--	2	2	1	1	1
Russian Hi-Frequency Induction	T5	--	4	3	--	9	9	--	8	8	3	3	3
Russian Hybrid Plasma	T6	--	6	6	--	7	8	--	7	7	--	6	6
Plasma Hearth Process	T7	--	7	7	--	5	6	--	5	5	--	7	7
Plasma Centrifical Furnace	T8	--	8	7	--	5	6	--	6	6	--	8	8
Vortec Combustion	T9	--	9	9	--	8	5	--	8	8	--	8	8
Microwave Melters	T10	--	9	9	--	10	10	--	8	8	--	8	8

Table 4.3

Looking at the rankings by expert in Table 4.3 only makes the similarities between A, B, and C's rankings more obvious. What differences there are will be discussed below.

4.2 *Results Grouped by Technical Risk Estimate*

4.2.1 *First Estimate.* Figure 4.1 shows the different utilities generated by the three sets of preferences for the technology estimates provided by the first expert. The technologies are shown in order of B's rankings, from #1 at the bottom to #10 at the top of the graph. The length of the

bars show the large differences in magnitude between the different "decision maker's" utilities. The technologies are ranked based on each "decision maker's" utility individually, however, so only the relative differences within A, B, or C's preferences are relevant. The relative positioning of the technologies are almost identical despite their different utility surfaces.

B and C differ in ranking AC Arc Melters (50%, 50%) vs. the Russian Hi-Frequency Induction method and In Situ Vitrification (75%, 25%) — C gives more value to the high P(dev) - low P(use) combination than B does. The difference between B and C on the Plasma Hearth Process and the Plasma Centrifical Furnace also illustrates something interesting. C gives them nearly the same utility of .019 (rounded off), despite having different attributes. These two technologies lie on an indifference curve for C, but not for B.

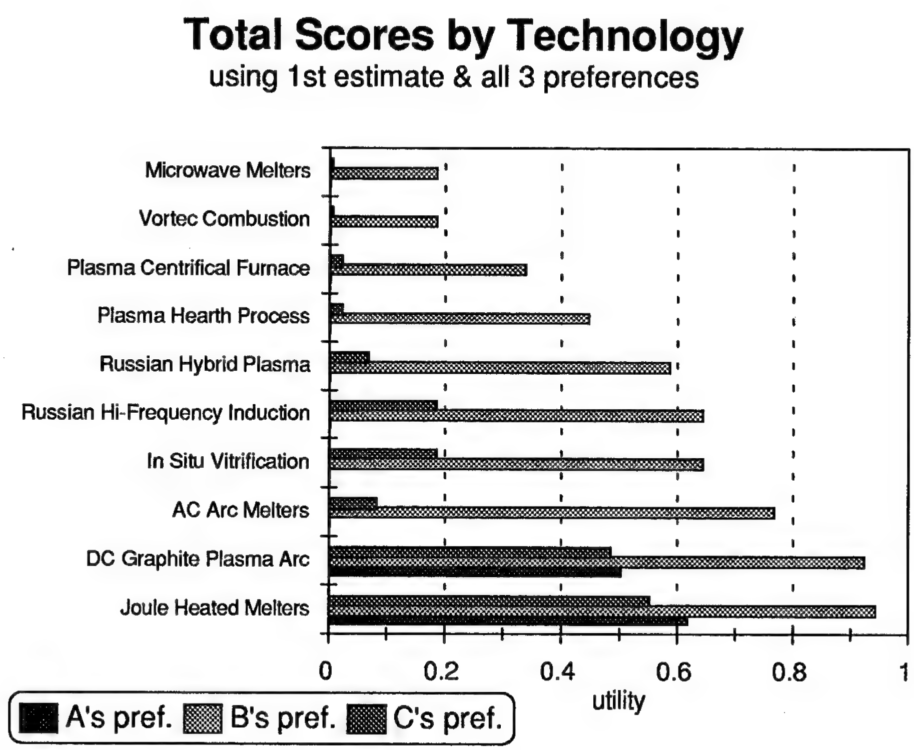

Figure 4.1

Figures 4.2 through 4.4 show the indifference curves of A, B, and C combined with the estimated likelihoods of successful development and use provided by the first expert. Again, the colored lines represent the utility contours at 0.1 intervals, starting with the yellow at the lowest left and climbing hight as one moves to the upper right. A's indifference curves clearly show how only T1 and T2 are viable candidates in his judgement. The difference in rank between T3 and the T4/T5 pair can also be easily seen in B's and C's graphs.

Figures 4.5 - 4.7 are the succinct culmination of the utility assessment process. The choices between the different alternatives are clearly visible. The shape of the utility the trade-offs the decision maker is willing to make between the two technical risk attributes to get the best-valued alternatives. The different technologies can be separated into different groupings, like "acceptable/unacceptable" or "high risk/medium risk/low risk," as desired by drawing contour lines. The differences between the three "decision makers'" values are also easily seen from A's flat, discontinuous shape to B's concave surface to C's convex one. The sensitivity of the rankings to changes in one or both attributes is easy to see from the color contours. For example, T3 would advance in rank in front of T4 and T5 with respect to C's preferences if its estimated likelihood of success improved by only 10% or so, while T7 would require a vast improvement in P(dev), P(use), or both before C would prefer it to T4 and T5.

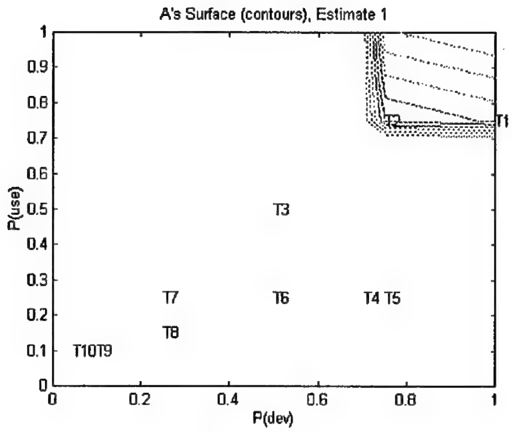

Figure 4.2

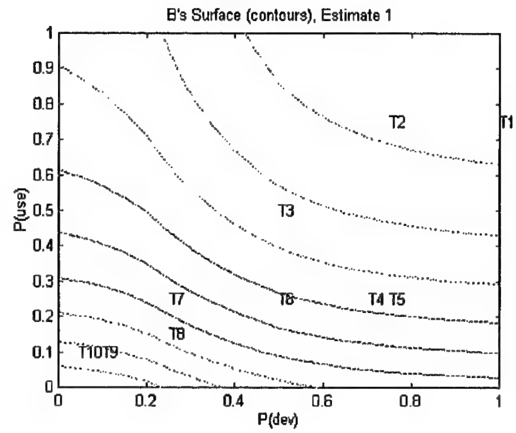

Figure 4.3

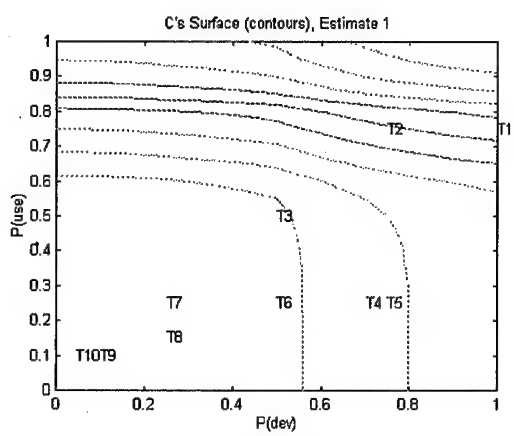

Figure 4.4

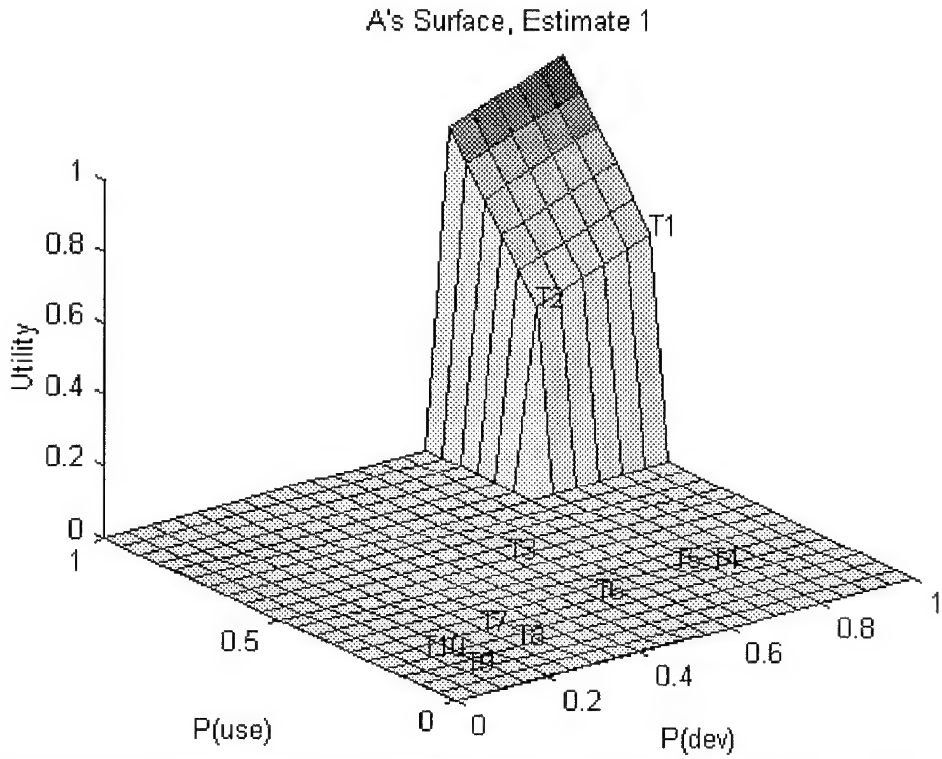
A's Surface, Estimate 1
Utility
1
0.8
0.6
0.4
0.2
0
T1
T2
T3
1
0.5
0
P(use)
0
0.2
0.4
0.6
0.8
1
P(dev)

Figure 4.5

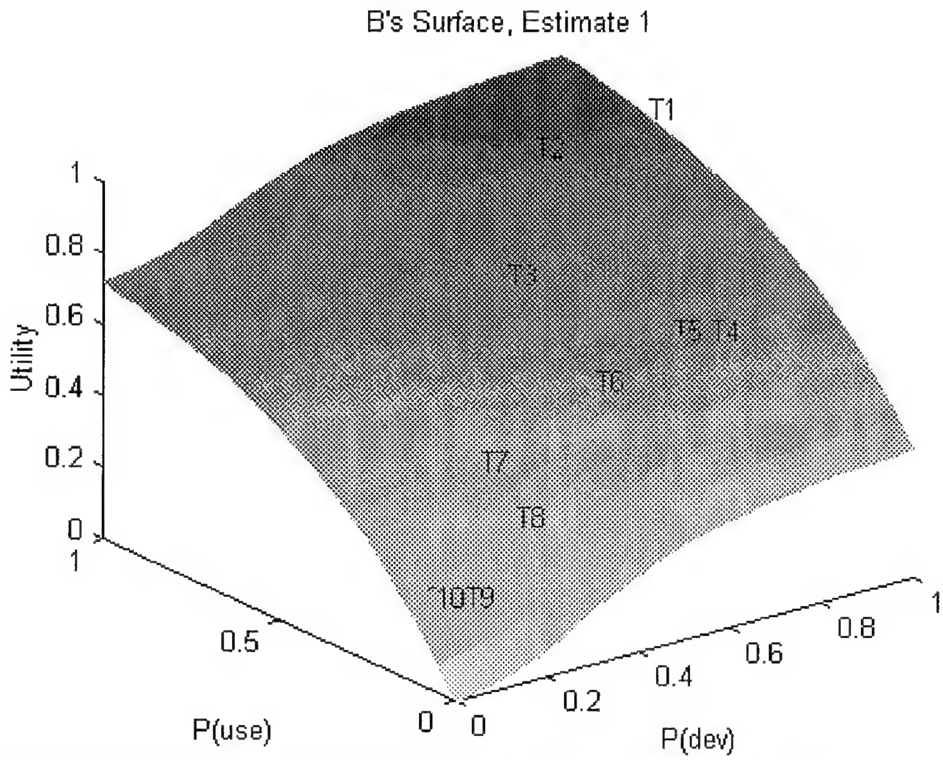
B's Surface, Estimate 1
Utility
1
0.8
0.6
0.4
0.2
0
T1
T2
T3
T5 T4
T6
T7
T8
T10T9
1
0.5
0
P(use)
0
0.2
0.4
0.6
0.8
1
P(dev)

Figure 4.6

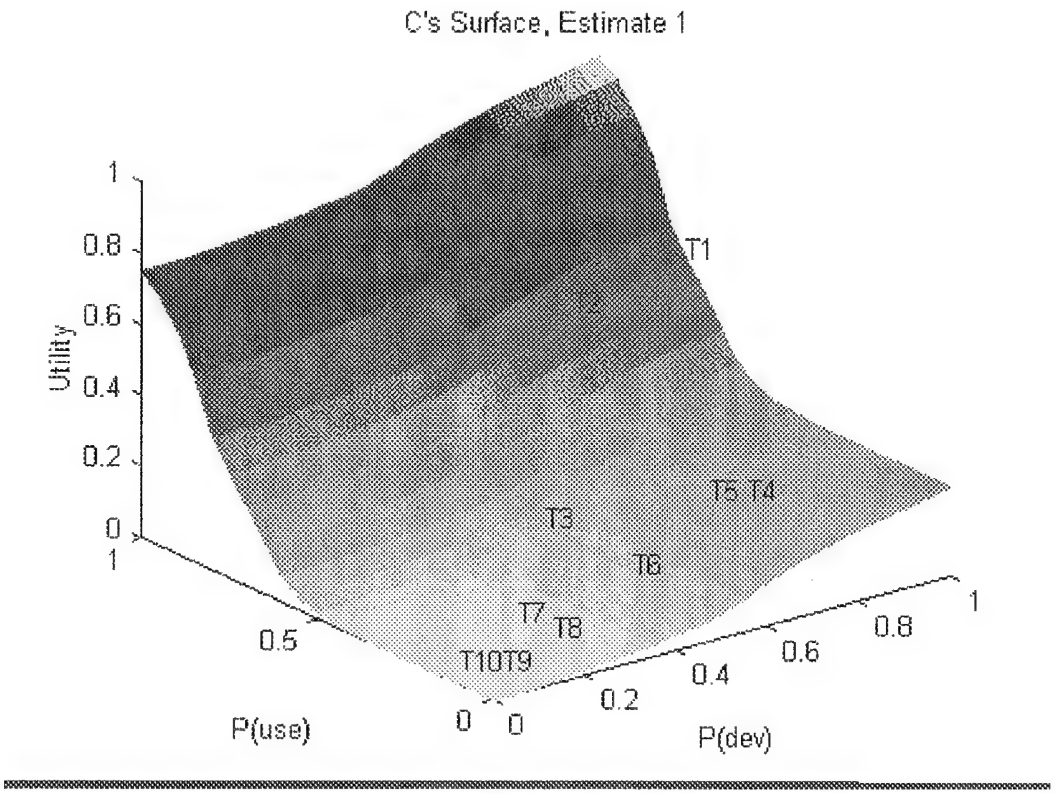
C's Surface, Estimate 1
Utility
1
0.8
0.6
0.4
0.2
0
T1
T5 T4
T3
T6
T7
T8
T10T9
1
0.5
0
P(use)
0
0.2
0.4
0.6
0.8
1
P(dev)

Figure 4.7

4.2.2 *Second Estimate.* The second expert had rather different views of the ten technologies' technical risk factors than the first. As one can see from Table 3.1, many of the estimated attributes changed. Consequently the ranking of the technologies has changed. The only disagreement between B and C's rankings, however, is that C thought fairly highly of Vortec Combustion, coded T9, compared to B's #5-#7 technologies (T8, T7, & T6, respectively). A look at the contour plots below reveals that the difference results from C placing practically no value on any technology with a P(dev) of less than 48% and a P(use) of less than roughly 60%. The yellow-colored indifference curve corresponds to a combined utility of .1, which is consistent with the utilities shown in Figure 4.8.

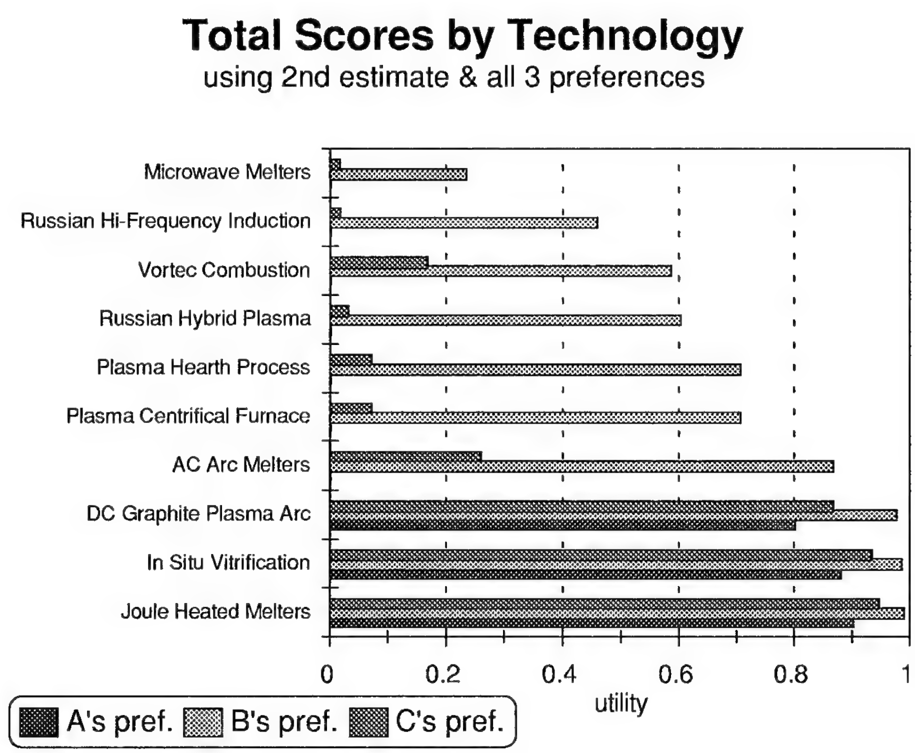

Figure 4.8

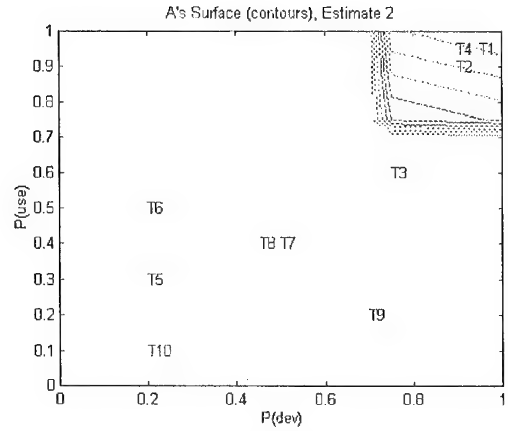

Figure 4.9

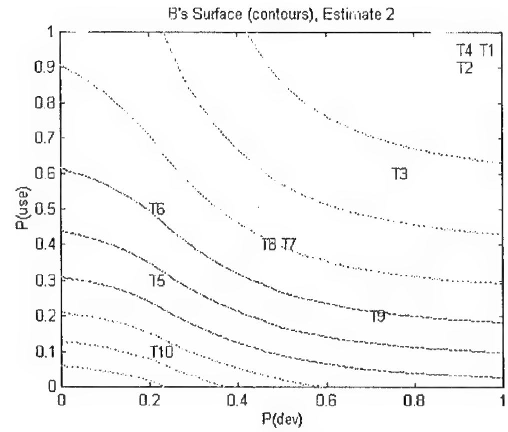

Figure 4.10

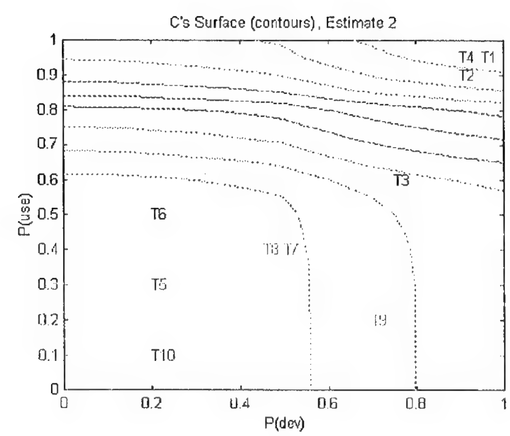

Figure 4.11

The tight cluster of T1, T2, and T4 near the upper corner of the utility surfaces results in nearly equivalent utilities. Other criteria are required should it be necessary for these "decision makers" to distinguish between them. B's relative tolerance for treatment technologies expected to be only moderately successful is shown here by the scattering of mid-range technologies (T3, T8, T7, T6, T9, & T5) across his concave utility surface. The convexity of C's surface reflects his contrasting intolerance for mediocre technologies. His preference for T9 over T8, T7, and T6 is easy to see, while B's preference for T8 and T7 is equally as evident.

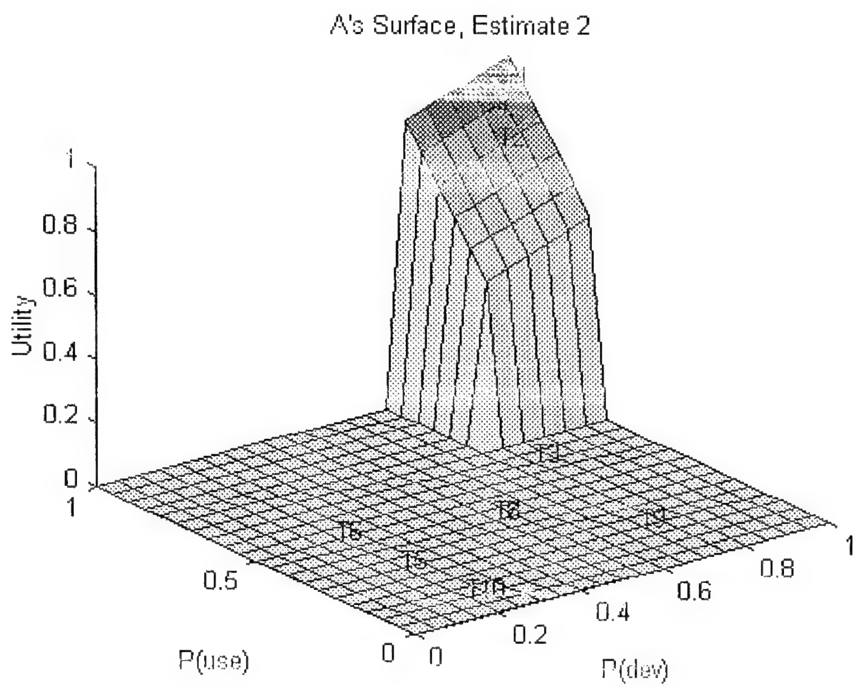

Figure 4.12

T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
Joule Heated Melters	DC Graphite Plasma	AC Arc Melters	In Situ Vitrification	Russian Hi-Freq. Induction	Russian Hybrid Plasma	Plasma Hearth Process	Plasma Cent. Furnace	Vortec Combust.	Micro-wave Melters

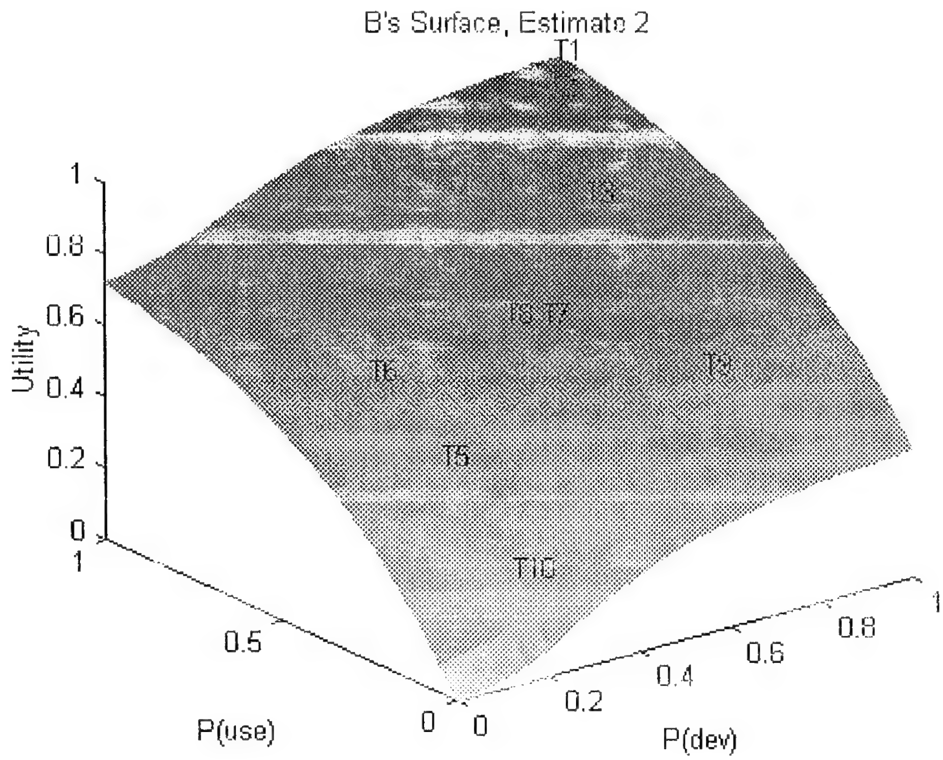

Figure 4.13

T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
Joule Heated Melters	DC Graphite Plasma	AC Arc Melters	In Situ Vitrifi-cation	Russian Hi-Freq. Induction	Russian Hybrid Plasma	Plasma Hearth Process	Plasma Cent. Furnace	Vortec Combust.	Micro-wave Melters

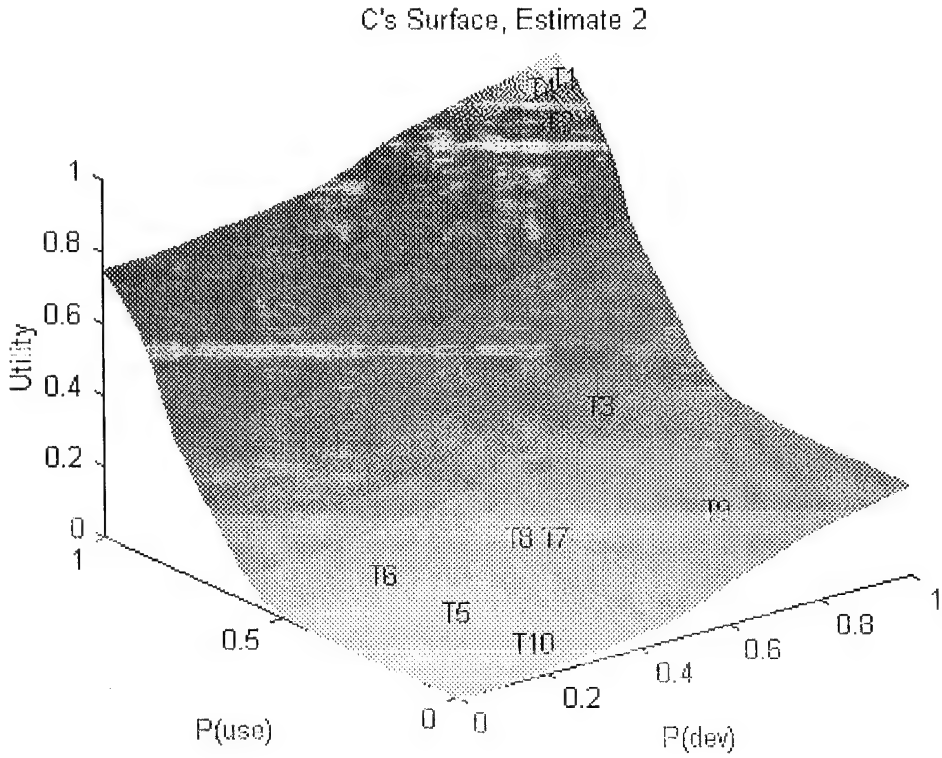

Figure 4.14

4.2.3 *Third Estimate.* The third expert was generally more conservative in his estimates of P(dev) and P(use), with correspondingly lower utilities across the board. Figure 3.3 shows how the estimates strung the technologies in a rough line between (0,0) and (1,1). One would expect rankings to correspond to the technology's position in this "string," and they do.

T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
Joule Heated Melters	DC Graphite Plasma	AC Arc Melters	In Situ Vitrifi-cation	Russian Hi-Freq. Induction	Russian Hybrid Plasma	Plasma Hearth Process	Plasma Cent. Furnace	Vortec Combust.	Micro-wave Melters

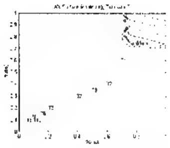

Figure 4.16

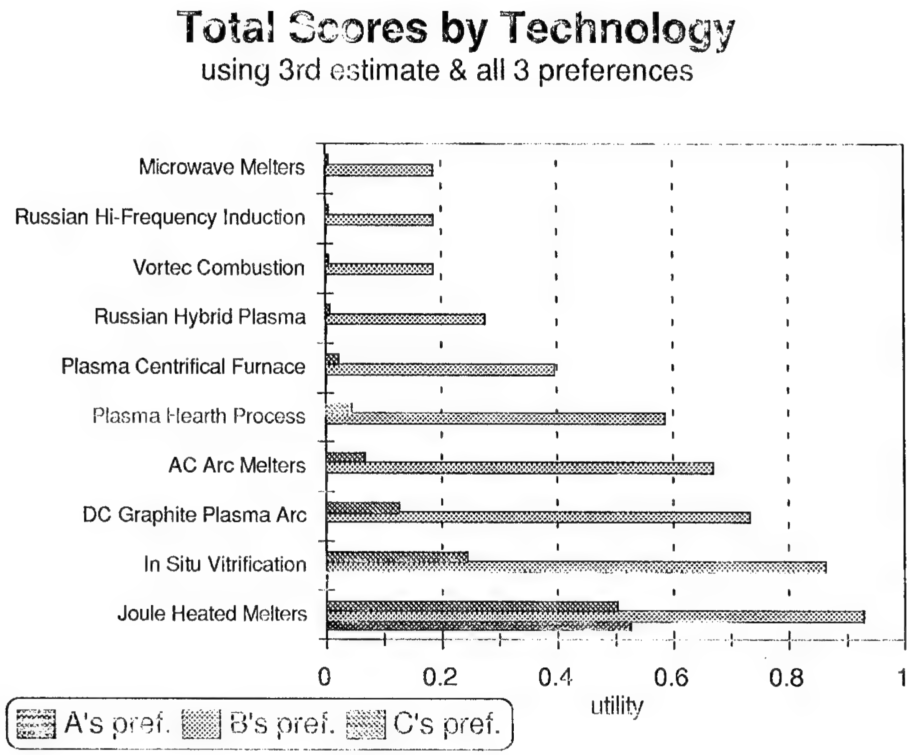

Figure 4.15

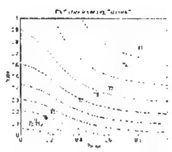

Figure 4.17

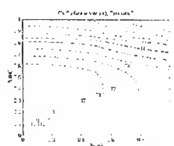

Figure 4.18

T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
Joule Heated Melters	DC Graphite Plasma	AC Arc Melters	In Situ Vitrifi-cation	Russian Hi-Freq. Induction	Russian Hybrid Plasma	Plasma Hearth Process	Plasma Cent. Furnace	Vortec Combust.	Micro-wave Melters

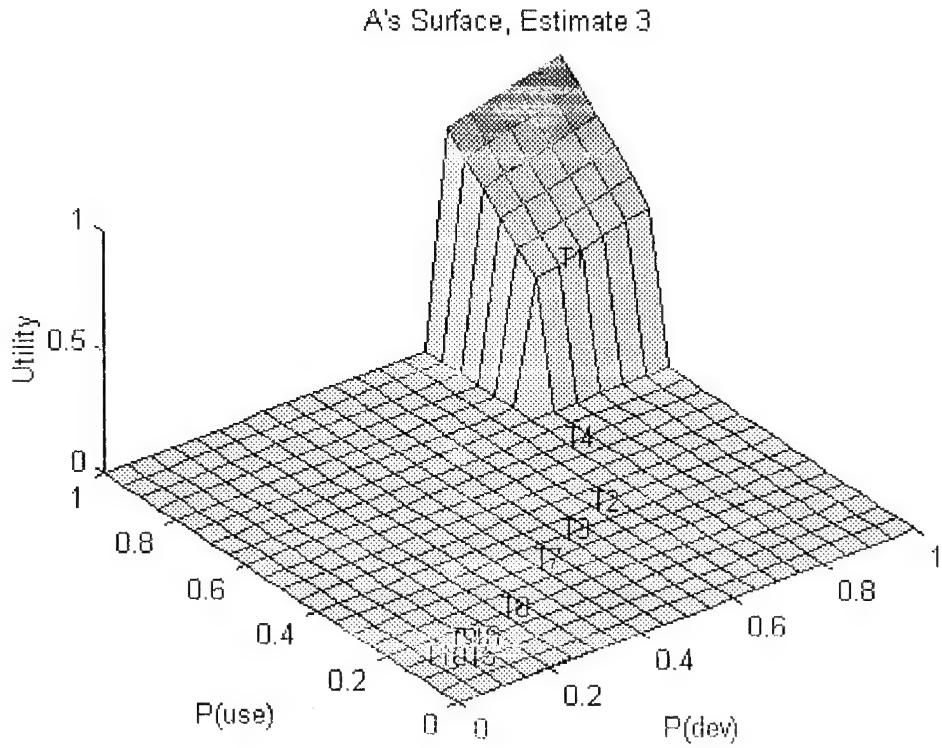

Figure 4.19

This expert's estimates are not so interesting. Since every technology in the "string" has a better P(dev) and P(use) than the one immediately following, the choices are clear. This situation, when one alternative is clearly better than others, is called *dominance* [Clemen,1991:88, 437]. Here we can say that T1 dominates all the other candidate technologies, T4 dominates the remaining ones, and so on for this estimate. Dominance greatly simplifies decisions when it occurs.

T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
Joule Heated Melters	DC Graphite Plasma	AC Arc Melters	In Situ Vitrifi-cation	Russian Hi-Freq. Induction	Russian Hybrid Plasma	Plasma Hearth Process	Plasma Cent. Furnace	Vortec Combust.	Micro-wave Melters

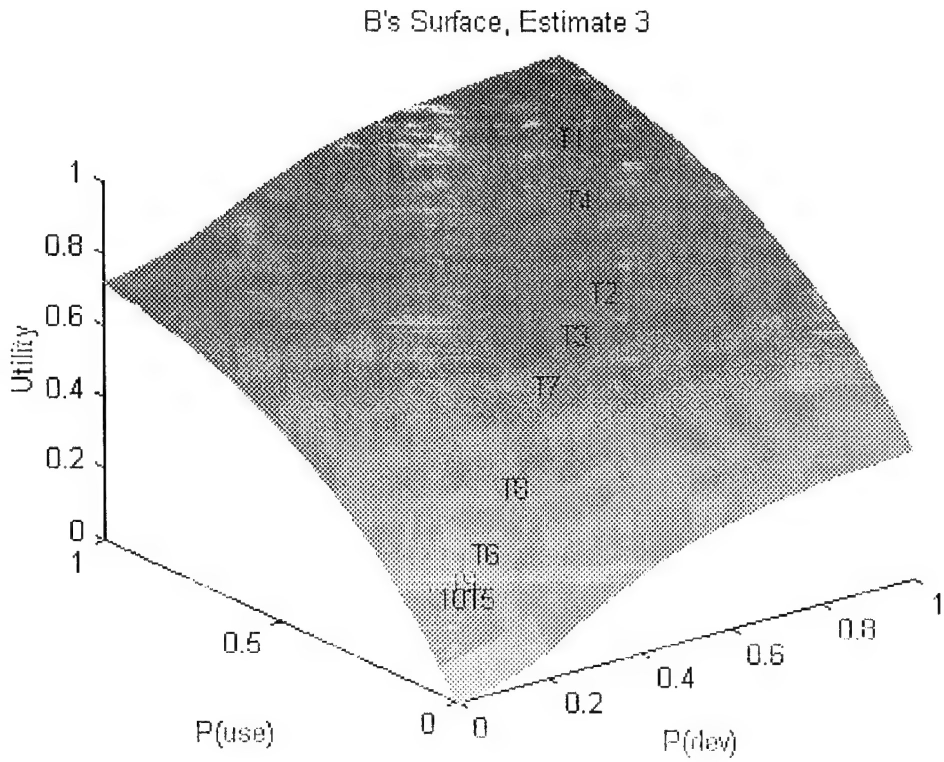

Figure 4.20

T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
Joule Heated Melters	DC Graphite Plasma	AC Arc Melters	In Situ Vitrifi-cation	Russian Hi-Freq. Induction	Russian Hybrid Plasma	Plasma Hearth Process	Plasma Cent. Furnace	Vortec Combust.	Micro-wave Melters

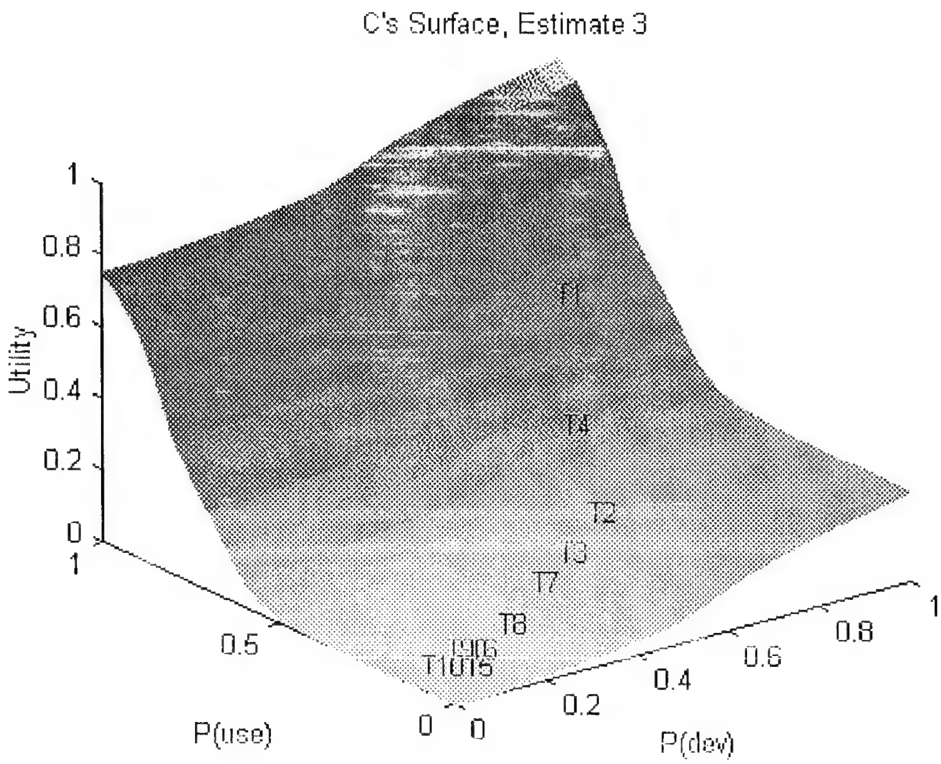

Figure 4.21

4.2.4 *Fourth Estimate.* The fourth expert was more optimistic with his estimates than the third was, but his estimates also form a kind of "string" (see Figure 4.4). This "string" curves out in a rough parabola, with every technology dominating its predecessor. A, B, and C all agree on the rankings of these technologies. There are several technologies with the same risk estimates, making other criteria the distinguishing factors.

T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
Joule Heated Melters	DC Graphite Plasma	AC Arc Melters	In Situ Vitrification	Russian Hi-Freq. Induction	Russian Hybrid Plasma	Plasma Hearth Process	Plasma Cent. Furnace	Vortec Combust.	Microwave Melters

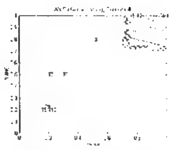

Figure 4.23

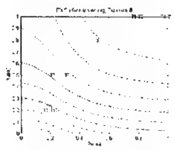

Figure 4.24

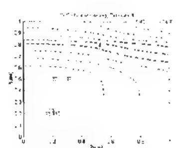

Figure 4.25

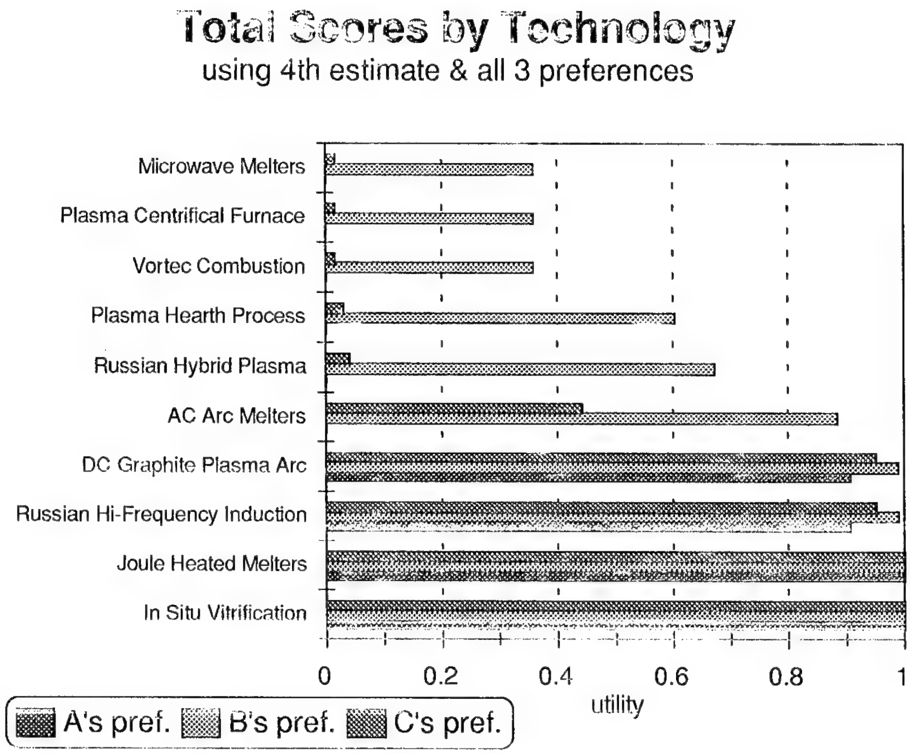

Figure 4.22

T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
Joule Heated Melters	DC Graphite Plasma	AC Arc Melters	In Situ Vitrifi-cation	Russian Hi-Freq. Induction	Russian Hybrid Plasma	Plasma Hearth Process	Plasma Cent. Furnace	Vortec Combust.	Micro-wave Melters

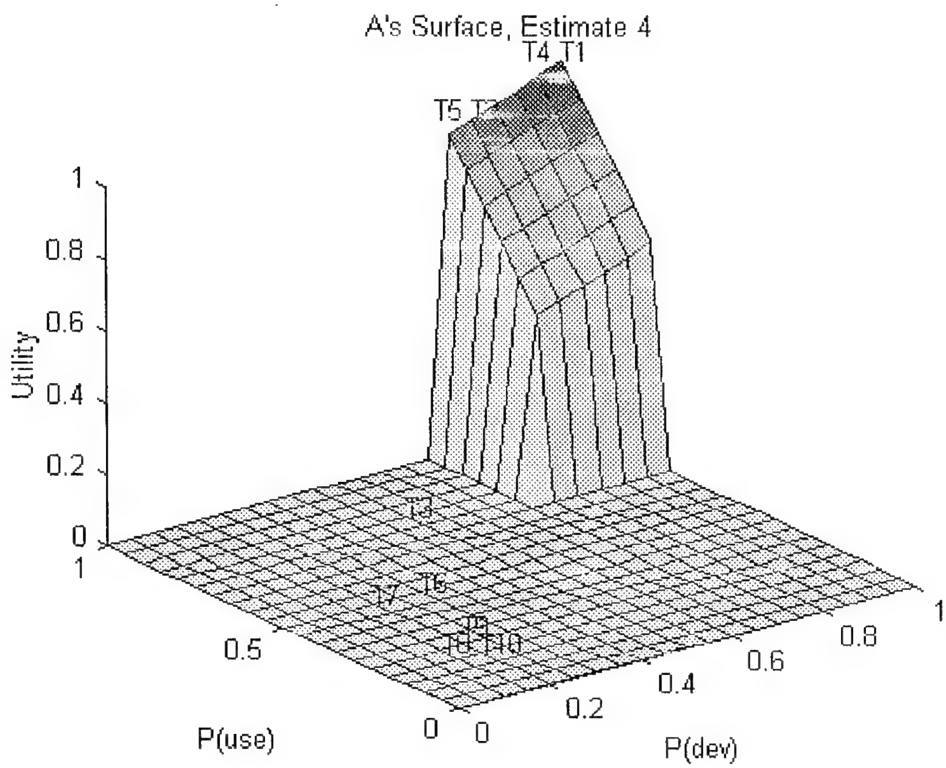

Figure 4.26

T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
Joule Heated Melters	DC Graphite Plasma	AC Arc Melters	In Situ Vitrifi-cation	Russian Hi-Freq. Induction	Russian Hybrid Plasma	Plasma Hearth Process	Plasma Cent. Furnace	Vortec Combust.	Micro-wave Melters

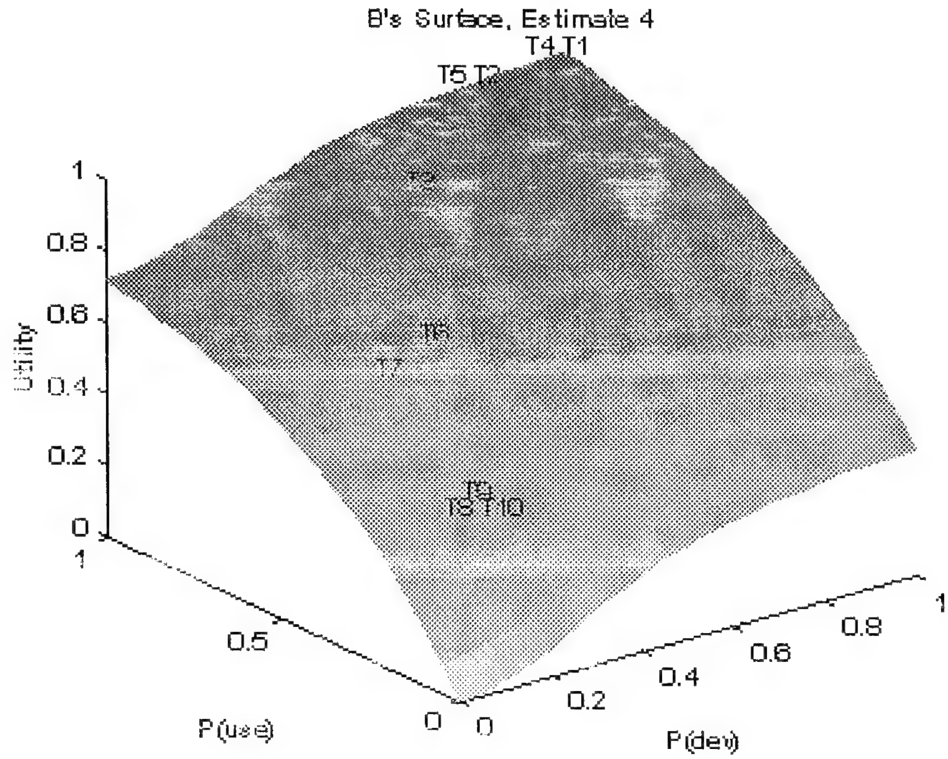

Figure 4.27

T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
Joule Heated Melters	DC Graphite Plasma	AC Arc Melters	In Situ Vitrifi-cation	Russian Hi-Freq. Induction	Russian Hybrid Plasma	Plasma Hearth Process	Plasma Cent. Furnace	Vortec Combust.	Micro-wave Melters

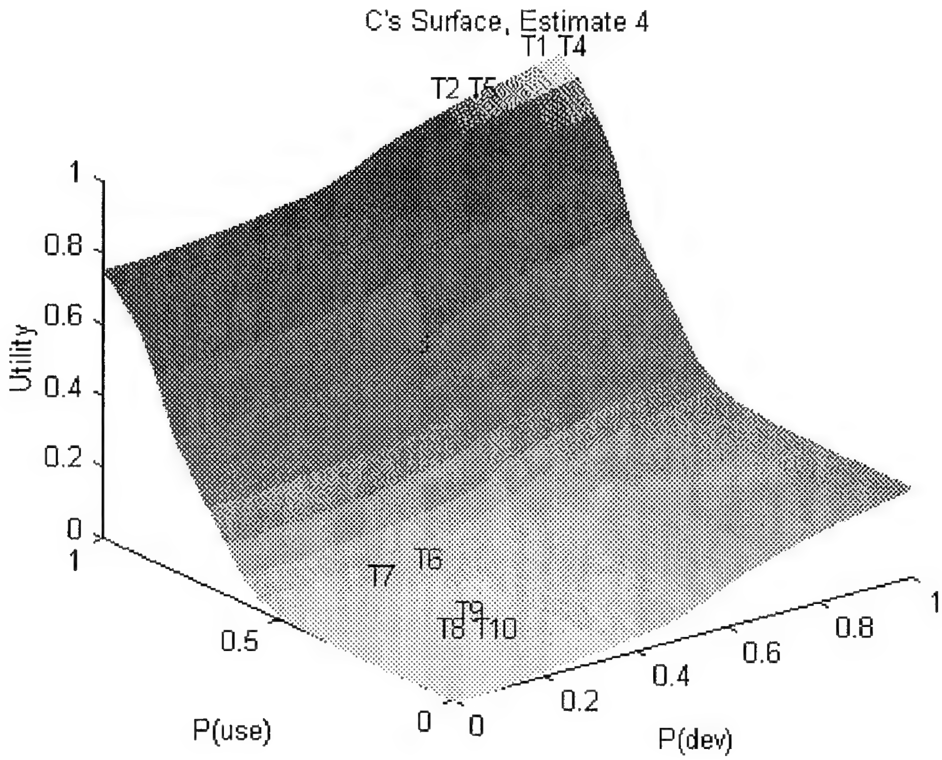

Figure 4.28

4.3 *Sensitivity Analysis*

The results summarized in Table 4.2 are very much the same for all three "decision makers" and experts' estimates, despite the different utility surfaces of A, B, and C. One reason for this similarity of rankings is that two of the technology attribute estimates have almost every technology dominated by its immediate predecessor. Any utility surface would generate the same rankings for the third and fourth estimates.

T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
Joule Heated Melters	DC Graphite Plasma	AC Arc Melters	In Situ Vitrification	Russian Hi-Freq. Induction	Russian Hybrid Plasma	Plasma Hearth Process	Plasma Cent. Furnace	Vortec Combust.	Microwave Melters

4.3.1 *Russian Hi-Frequency Induction Method.* The agreement of the rankings between "decision makers" and expert estimates is striking when Table 4.2 is studied. One apparent inconsistency, however, is the difference in rank of the Russian Hi-Frequency Induction method, T5, between estimates 1 & 4 and estimates 2 & 3. In estimate 1, T5 is ranked 4th (by B) or 3rd (by C). In estimate 4, it is 3rd for all three "decision makers." However, T5 is ranked 9th in estimate 2 and 8th (in a three way tie for last) in estimate 3 by B and C.

The reason for this anomaly can be seen in Table 3.1. The P(dev), P(use) numbers are (75, 25) in the first estimate, (80, 100) in the fourth, (20, 30) in the second, and (10, 10) in the third. This is the widest disagreement between the four experts and is worth further analysis.

If one examines the other candidate technologies ranked about T5, one can see the changes in P(dev) and P(use) that would be necessary to raise or lower T5's ranking as a measure of how sensitive T5's rank is to the estimated risk factors. Table 4.4 lists what it would take in positive and negative adjustments to each expert's P(dev) and P(use) to change the rank of T5.

Table 4.4 requires some explanation. It should be read down each column, one for each expert's estimates, while looking at the rows associated with one "decision maker's" preferences at a time. Only one attribute was allowed to change at a time. The rows show what change to T5's P(dev) or P(use) would be necessary to force a change in rank. The changes in the attributes raise or lower T5's utility to the same value as the next highest or lowest ranked technology, thereby changing T5's rank.

One-Way Sensitivity Analysis for Russian Hi-Frequency Induction

changes in P(dev) or P(use) that change the rank of the technology

		estimate:	1	2	3	4
A's preferences	raise	Δ P(dev)	next below threshold	next below threshold	next below threshold	+ 20%
		Δ P(use)	+ 50%	next below threshold	next below threshold	can't
	lower	Δ P(dev)	at bottom	at bottom	at bottom	0
		Δ P(use)	at bottom	at bottom	at bottom	0
B's preferences	raise	Δ P(dev)	can't	+ 21%	+ 16%	+20%
		Δ P(use)	+ 16%	+ 17%	+ 07%	can't
	lower	Δ P(dev)	0	can't	at bottom	0
		Δ P(use)	0	- 20%	at bottom	0
C's preferences	raise	Δ P(dev)	can't	+ 12%	+ 06%	+ 20%
		Δ P(use)	+ 50%	+ 20%	+ 31%	can't
	lower	Δ P(dev)	0	- 01%	at bottom	0
		Δ P(use)	0	- 20%	at bottom	0

Table 4.4

Since so many technologies lie below A's 75% thresholds, in many cases T5 has the same zero utility as a technology with a higher P(dev) or P(use). In these cases it is meaningless to consider raising T5's rank, signified by the entry "next below threshold." "At bottom" refers to situations where T5 is already at the bottom of the technology rankings and therefore can not lower in rank. It is possible that no improvement in one attribute can improve the rank of T5 because even a 100% attribute would not improve T5's utility enough to reach the next highest

technology. Conversely sometimes the next lowest technology's utility is too low to be reached by changing only one attribute. A "can't" entry refers to these cases. Finally, if T5 has the same attributes as another technology, even an infinitesimal change in an attribute would change the rank of T5. This is signified by a "0."

For example, if one was examining the sensitivity of T5's rank using B's preferences in estimate 2, one would see a rise in rank by increasing P(dev) by 21% (to 41%) or by increasing P(use) by 17% (to 47%). One couldn't lower T5's rank by dropping P(dev), but it is possible to drop T5 to last place by decreasing P(use) by 20% (to 10%).

The most sensitive cases are those where the Russian Hi-Frequency Induction method shares the same P(dev) and P(use) estimates with other treatment technologies. Readdressing these estimates with additional care would be advisable, since any change will cause a shift in rankings. Other cases where the necessary changes are less than 10% should be treated with similar care. The most interesting case is with the first expert's estimates, where T5 is in the top four technologies and only an increase of 16% would be needed in P(use) to shift B's rankings. The situation in estimate 4 is not as interesting, since T5's P(dev) would have to rise to 100% to increase in rank, joining T1 and T4 at complete certainty (100%, 100%).

4.3.2 *Vortec Combustion in Estimate Two.* One other anomaly worth investigating is the difference in Vortec Combustion's ranking (T9) using the second expert's estimates of (70%, 20%) and B and C's preferences. B rates T9 as #8, while C gives it #5. That is a significant difference when using the same attributes.

B's utility function gives T9 a 0.585 utility, which is fairly low for B. C gives T9 a 0.166 utility, enough to distinguish it from T8, T7, and T6 as mentioned in section 4.2.2. An examination of Figures 4.10 and 4.11 or 4.13 and 4.14 show how C's relatively lower value for low P(dev) estimates lowers the other technologies' ranks relative to B's rankings. B's indifference curves in Figure 4.10 show the blue .6 utility contour passes just over T9's coordinates but beneath T6, T7, and T8.

Since the indifference curves seem to suggest the difference is caused by C's higher value for P(dev) than B, a one way sensitivity analysis on the weights of the multi-attribute utility functions seems in order. Again, the idea is to find the point where two technologies have the same total utility. Here T9 will be checked against T6 and T7/T8 to find levels of k_d and k_u where the utilities are equal. The results are summarized in Table 4.5 below.

C has an additive multi-attribute utility function (see equation 1 in section 1.2.4.1). This form requires $k_d + k_u = 1$. Therefore we only need to examine the one case. Since B's multi-attribute utility function is has a multilinear form (see equation 2 in section 1.2.4.2), k_d and k_u do not have to sum to 1, so they have to be analyzed separately while the other stays constant.

Sensitivity Analysis for Vortec Combustion in Estimate 2

changes in weights that force T9 to change ranks with other technologies

C's utility function ($k_u = 1 - k_d$)		
	current value	weights needed to lower T9's rank
k_d	0.25	0.01
k_u	0.75	0.99
resulting utility of T9	0.166	0.007
B's utility function ($k_u \neq 1 - k_d$)		
	current value	weights needed to raise T9's rank
k_d	0.3863	0.457
holding k_u constant	0.7726	0.7726
$1 - k_d - k_u$	-0.1589	-0.2296
resulting utility of T9	0.601	0.64
k_u	0.7726	0.7125
holding k_d constant	0.3863	0.3863
$1 - k_d - k_u$	-0.1589	-0.0988
resulting utility of T9	0.601	0.599

Table 4.5

The results in Table 4.4 need some interpretation. To drop Vortec Combustion in C's rankings, practically no importance could be placed on the risks of successful development. The only thing that could matter would be the estimated success of the technique in the field. This is unrealistic and can be dismissed as a possibility. Therefore C would never really change his ranking of Vortec Combustion if the second expert's P(dev) and P(use) estimates were used.

The results for B are less clear. Since his combined utility function is not additive, it is more difficult to interpret what the weights mean. When changing k_d to cause T9 to switch ranks with T6, more importance is placed on P(dev) than before. Less importance is placed on P(use) when changing k_u. While this is consistent, the full picture must include the $(1 - k_d - k_{u)}$ term. Using the concepts of complements and substitutes introduced in section 1.2.4.2.1, one can see that B treats P(dev) and P(use) as substitutes — a shortfall in one attribute can be made up for by a high estimate in the other. This relationship becomes more pronounced when k_d is raised, making the attributes even more able to act as replacements for each other. When k_u is lowered, however, the $1 - k_d - k_u$ becomes almost insignificant, suggesting that B's ranking of the treatment technology is sensitive to his original dismissal of additive independence.

V. *Conclusions*

While the risks involved with procuring emerging technologies are large, new remediation techniques must still be developed in order to affordably achieve the long-term remediation objectives of the Department of Energy. Minimizing the technical risks, as well as the financial and environmental costs they induce, is one way the Office of Technology Development is meeting these objectives. This requires intelligent decision making about the candidate technologies, since these decisions will not be simple. The models developed in this study show how one set of risk trade-offs can be made with the assistance of decision analysis techniques.

Two important aspects of technical risk were examined from a DOE manager's viewpoint. The risk that a technology being developed would not be ready for use in the field requires that a manager face the possibility of having expended critical time and funds on a technique that cannot fulfill scheduled remediation deadlines. The risks of failure in use carry graver consequences, with possibilities of wasted effort and violated regulatory standards or even of inadvertent exposure of radioactive and hazardous materials to people and the environment. Other concerns, such as development cost and schedule risks, were not addressed in this study.

5.1 *The Assumptions*

The structure of the modeled preferences in this study depends on the definitions of the two technical risk measures, P(dev) and P(use). Based upon the definitions of P(dev) and P(use), and the assumptions within them, the utility functions developed in this study are useful to map the trade-offs between development and implementation risk. The rankings of the ten treatment

technologies were much more sensitive to the various expert estimates than to these assumptions, and so further refinement and sophistication was deemed unnecessary considering the coarseness of the data.

5.1.1 *Development Risk.* The risk of successful development was defined as likelihood that a technology would have completed research and development by a certain date and be ready for employment in the field. This probability is defined to be independent of the time spent in R&D, through the assumption that the performance standards the technology must pass in the demonstration and validation stage remain the same throughout R&D. The estimates of this likelihood do not take any budgetary effects into account — increasing or decreasing the funding to a development project can accelerate or retard the progress toward a commercializable product, effectively raising or lowering estimates of P(dev). However, the difficulty of predicting from present day knowledge future overall funding fluctuations or the effects of prioritizing certain projects over others practically precludes the inclusion of such items into this study.

5.1.2 *Implementation Risk.* The risk of successful use is carefully separated by its definition from the duration of a technology's R&D period. This is to exclude unknowable factors from this study, since the dependence of a technology's future performance on R&D that has not been completed or, in some cases, even begun, is difficult to estimate. Thus the definition of the probability of successful field use is the likelihood of a technology that meets its demonstration and validation standards accomplishing its designed purpose. Note that the nature of failure in actual use is left unspecified — while some failures may be relatively minor, requiring perhaps that another technique must be used to finish a job left uncompleted, there is the potential

for catastrophic accidents involving inadvertent exposure to toxic or radioactive waste. The prediction of possible consequences of an unknown failure are beyond the scope of this study. The nature of the landfill itself is left out of these P(use) estimates. The estimates of P(use) must be conditional on the assumption that these preliminary site assessments are correct, since the potential effects of inaccurate preliminary site characterization are unknowable.

5.1.3 *Subjective Probability Estimates*. Since this study focused on modeling decision makers' attitudes toward technical risk, very little attention was paid to the technology attributes estimated from expert opinion. The subject of subjective probability estimation is too broad to be summarized here, but one thing is clear. Technology forecasting of innovative items has no other choice but to use expert opinion as the source of needed information simply because no objective data exists for emerging technologies. Expert estimates are often biased and inaccurate [see Hudak, 1994; King & Wilson, 1967; King, et. al., 1967; Biery, et. al., 1994]. Errors are even more likely when dealing with innovative technology, since the developers of the technology themselves may be the only one possessing the necessary understanding to give credible opinions, and they most often have optimistic views on the matter to justify their work to themselves and their sponsors. Despite the inaccuracy of expert opinion and subjective probability estimates, there is no other alternative to using it.

The difference in rankings of the ten treatment technologies in section 4 of this report result more from the differences in experts' estimates of P(use) and P(dev) than from the preference structures of the "decision makers." The implications of this are clear: when applying the methods discussed in this study to a real decision, ***at least*** as much attention must be placed

on getting quality estimated risk attributes as on correctly modeling the decision maker's preferences. The old computer programming rule, "garbage in, garbage out" definitely applies.

5.2 *The Results*

Based on the limited sample utilized in this study, the best choices for low technical risk treatment technologies remained Joule Heated Melters, In Situ Vitrification, DC Graphite Plasma Arcs, and AC Arc Melters (T1, T4, T2, and T3, respectively), across the majority of combinations of experts' estimates and "decision makers'" utility surfaces. These technologies have the least anticipated technical risk for treatment processes scheduled to begin seven years from now.

Despite the different viewpoints of the three interviewed "decision makers" and the resulting mathematical descriptions of their values on technical risk, the rankings of candidate treatment technologies remained consistently similar. Each of the three contractor's utility surfaces were assessed independently. This suggests that using multi-attribute utility theory to model this aspect of a technology selection decision has at least "face validity," and that one could reasonably apply these methods to other similar decision problems.

The Russian Hi-Frequency Induction technology was the only candidate whose ranking greatly varied between expert estimates (see section 4.3.1). The estimates for this technology showed the only serious inconsistency between experts. Since this technology was ranked in the top four for two of the experts' estimates, this particular technology should be examined with care to analyze its technical risks before final selection of technologies is made. This is the issue where additional study will have the greatest impact on the decision.

The three-dimensional graphs in section 5 of this report were found to condense many of the issues of risk tolerance and technology comparison into a concise form that is easy to understand. Illustrations of this sort can summarize results that would otherwise take several pages of tables and easily misunderstood explanation to present. The sensitivity of the rankings of alternatives to changes in their attributes are obvious and easily explained.

5.3 *How to Use This Study*

5.3.1 *Selecting a Treatment Technology.* By examining the utility surface plots for each set of estimates in section 4, one can see how close the lower ranked technologies come to the best ones in order to anticipate how other non-risk factors might change a decision maker's order of preference. For example, when considering the second expert's estimates as depicted on Figures 5.12, 5.13, and 5.14, one can easily see that A would never consider T3 as a potential candidate, while B would see T3 as only somewhat less preferable than T2, T4, or T1. C views T3 as more suitable than lesser ranked technologies, but other considerations would have to carry very high weight before he would prefer it in place of the three substantially less risky alternatives.

5.3.2 *Models of "Decision Maker" Preferences.* Just as the various estimates of the development and implementation risks for the ten treatment technologies shown in Figure 1.1 were applied to the three "decision makers'" utility surfaces, any set of technology alternatives can be ranked by use of the appropriate process' utility surfaces. The three contractors whose preferences were assessed had very different viewpoints (programmatic, waste site manager, and technology developer) and their utility surfaces could be applied as rough characterizations of decision makers who share those perspectives.

It should be noted that these utility functions are independent of any specific technology alternatives — unlike pairwise comparison methods like the Analytic Hierarchy Process (AHP), the utility functions described in section 2 are valid for all sets of potential candidates one might want to examine with regard to these attributes of technical risk, and do not have to be re-assessed whenever new candidates are added the way AHP results must be [Kloeber, 1992:15].

5.3.3 *Methodology Applied to Other Decisions*. This approach mapped the decision maker's value to quantified risk attributes of potential candidate technologies. Other attributes, such as cost or schedule estimates, could easily be examined in the same manner. All that is required is careful definition of the attributes, then an interview with the decision maker where his or her utility functions are assessed. Some follow-up work by the interviewing analyst is necessary afterwards to produce graphical summaries of the decision maker's utility functions and analysis of the resulting ranking of alternatives. In general, with proper background and software support, this is not an extremely difficult process to complete for relatively simple trade-offs, like that between developmental and implementation risk here.

One thing to emphasize, however, is that this kind of study is the result of a partnership between the decision maker and the analyst. In a sense, the analyst helps the decision maker quantitatively express his or her values for certain parts of the decision in order to make better overall choices. Utility curves are no replacement for the decision maker whose preferences are mapped — the decision maker "owns" the decision, while the analyst is providing a service whose ultimate quality is measured by satisfaction of the decision maker. Analysis of the sort described in this report can only illuminate part of the decision problem through quantitative means such as

utility theory. Other qualitative factors relevant to the decision, such as political or budgetary constraints, are left to the decision maker to sort out, since he or she is the best judge of their importance and impact.

While the graphs of the various utility curves and the candidate technologies are an important outcome of this work, the primary result has been the demonstration of multi-attribute utility theory to formalize a decision maker's feelings about technical risk, for use in remediation technology selections. The three interviews took about five hours total to accomplish, and yet provided enough information to develop a powerful model for analyzing investment decisions about emerging technologies. The encapsulation of the experience and preferences of upper-level managers is not perfect by any means, but a model like the ones developed in this project can help decision makers focus on the equally important qualitative issues. Together with other decision analysis tools, preference models based on utility theory can be applied to assist technology managers in making the tough choices necessary to carry out the Department of Energy's long-term environmental remediation program.

Appendix A — *"Decision Makers" and Experts*

The assistance of all involved with this project was greatly appreciated. The "decision makers" whose utilities were assessed were George Dewhirst, Paul Krumrine, and Dave Simpson, working at the Waste Policy Institute's field office at Aiken, South Carolina. The experts who provided their opinions about the ten treatment technologies were Drs. Leo Baetsle, Erwin Fenyves, William Prindle, and Henry Schreiger.

Appendix B — *Equations of Utility Curves*

The utility curves and surfaces shown in section III of this report were generated with the help of the *Logical Decisions for Windows*© program (*LDW*). After the single-attribute utility functions were assessed during the interview, they were transferred to *LDW*© by replicating the hand-drawn curves using the "Assess SUF" procedure. The weights for the multi-attribute utility functions were assessed using the on-screen procedures of *LDW*©. The weights and utility equations were then re-written into a spreadsheet to generate the data plotted in the report.

LDW© fitted the utility curves with either a linear or an exponential equation applied piece-wise across the range of the attributes. The exponential equation had this form:

$$y = a + b\, e^{c\,x} \qquad \text{(A-1)}$$

where x is the attribute in question. The linear equation had this form:

$$y = a + b\,x$$

These equations and the multi-attribute weights follow, for each "decision maker's" utility function shown in the report. If $c = 0$ in the following list, use the linear form.

A

all; $k_d = 0.2315$, $k_u = 0.7685$

P(dev) & P(use)	0	0	0	(0, 0.75)
	-1	2	0	(0.75, 1)

B

characterization; $k_d = 0.4137$, $k_u = 0.8273$

P(dev)	0.04003	-0.04003	-36.64	(0, 0.2)
	-0.05	0.04555	3.406	(0.2, 0.5)
	0.08571	0.001998	8.093	(0.5, 0.75)
	1	6.924E+08	-31.13	(0.75, 1)
P(use)	-0.0158	0.0158	7.68	(0, 0.5)
	1.011	-7.68	-6.563	(0.5, 1)

stabilization; $k_d = 0.2269$, $k_u = 0.4537$

P(dev)	0.04003	-0.04003	-36.64	(0, 0.2)
	-0.05	0.04555	3.406	(0.2, 0.5)
	0.08571	0.001998	8.093	(0.5, 0.75)
	1	6.924E+08	-31.13	(0.75, 1)

"Decision Maker" technology type & multi-attribute weights attribute	a	b	c	Range of Equation (from, to)
P(use)	-0.01286	0.01286	7.525	(0, 0.32)
	-0.5942	0.4663	1.376	(0.32, 0.62)
	1.018	-127.2	-8.78	(0.62, 1)
containment; $k_d = 0.3197$, $k_u = 0.6394$				
P(dev)	0.04003	-0.04003	-36.64	(0, 0.2)
	-0.05	0.04555	3.406	(0.2, 0.5)
	0.08571	0.001998	8.093	(0.5, 0.75)
	1	6.924E+08	-31.13	(0.75, 1)
P(use)	0	0.05	0	(0, 0.1)
	-0.3571	0.292	2.154	(0.1, 0.5)
	1.146	-2.856	-2.972	(0.5, 1)
removal; $k_d = 0.1771$, $k_u = 0.3543$				
P(dev)	0.04003	-0.04003	-36.64	(0, 0.2)
	-0.05	0.04555	3.406	(0.2, 0.5)
	0.08571	0.001998	8.093	(0.5, 0.75)
	1	6.924E+08	-31.13	(0.75, 1)
P(use)	-0.03242	0.03242	4.665	(0, 0.4222)
	-0.1245	0.7685	0	(0.4222, 0.62)
	0.3198	3.963E-08	21.95	(0.62, 0.73)
	1.061	-53.76	-6.78	(0.73, 1)
treatment & disposal; $k_d = 0.3863$, $k_u = 0.7726$				
P(dev)	-0.09497	0.09497	5.821	(0, 0.2)
	1.341	-1.745	-2.166	(0.2, 0.5)
	1.047	1.876	-3.687	(0.5, 1)
P(use)	1.125	-1.125	-2.197	(0, 1)
monitoring; $k_d = 0.0334$, $k_u = 0.0667$				

"Decision Maker" technology type & multi-attribute weights attribute	a	b	c	Range of Equation (from, to)
P(dev)	0	1	0	(0, 1)
P(use)	-0.3346	0.3346	1.203	(0, 0.76)
	2.856	-8.829	-1.738	(0.76, 0.82)
	1.019	-6.553E+04	-15.05	(0.82, 1)
C				
characterization, stabilization, containment, & monitoring; $k_d = 0.25$, $k_u = 0.75$				
P(dev)	-0.0035	0.0035	13.86	(0, 0.2)
	-0.0796	0.07007	3.175	(0.2, 0.5)
	1.329	-3.453	-2.351	(0.5, 1)
P(use)	-0.025	0.025	4.394	(0, 0.5)
	1.1	-8.1	-4.394	(0.5, 1)
removal, treatment, & disposal; $k_d = 0.25$, $k_u = 0.75$				
P(dev)	-0.0035	0.0035	13.86	(0, 0.2)
	-0.0796	0.07007	3.175	(0.2, 0.5)
	1.329	-3.453	-2.351	(0.5, 1)
P(use)	-1.0E+05	1.0E+05	15.32	(0, 0.6)
	-1.1	2	0	(0.6, 0.8)
	1.113	-538.2	-8.473	(0.8, 1)

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